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 to 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.

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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. There is little 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 and Federal biofuel tax credits, has created an exogenous shift in demand for U.S. *corn*, the main ingredient in U.S. ethanol production. We use this 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 to 2006 to study the 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 that there is indeed 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) testing procedure (DIDID, henceforth). 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 to, 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—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 is only about five miles in recent years. For comparison, the size of the median county in our sample is 416 square miles, or about twenty miles by twenty 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. We discuss these robustness tests in more detail below.

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 to 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. Furthermore, our results hold with (and without) state- or county-fixed effects, which rules out many alternative hypotheses centered on unobservable time-invariant factors driving our results.

Of course, 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- and county-fixed effects. In the county fixed effects regressions, only within-county time-series variation in deposits drives our 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 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 to 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 multivariate tests—which control for a variety of factors, including state- or county-fixed effects, population density, and meteorological conditions—provide similar results.

One potential concern is that of reverse causality: if a county experiences high crop yields, this will lead to more wealth for the farmers in the county, who may then deposit their wealth in local banks. In this case finance and productivity are linked, but finance follows (rather than 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 may 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 nonetheless indicative of greater access to finance. Second, we use an instrumental variables approach with lagged measures of access to finance serving as instruments for current access to finance. This instrumental variables approach forces the exogenous portion of access to finance to explain productivity. Both of these approaches leave all of our main conclusions unchanged and mitigate the concern that reverse causality drives our results.

Our results are robust to a variety of additional changes in our baseline tests. Using wheat as a control crop instead of soybeans, and including contiguous county bank deposits leave our results unchanged. Alternatively, directly controlling for systemic changes in productivity with measures of national labor productivity or other agricultural productivity benchmarks in a differences-in-differences test leaves our results unchanged. We also use a completely different demand shock—the sudden switch from sugar to high fructose corn syrup by major soft drink manufacturers in 1985—in conjunction with a different measure of access to finance based on bank branching deregulation (as in Jayaratne and Strahan (1996)) and find qualitatively similar results. In short, our results are robust to changes in our measure of access to finance, our control crop, our productivity benchmark, our event defining the natural experiment, general trends in farm productivity, and unobservable time invariant factors 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), Whited (2006), Chava and Roberts (2008)). And, like Bakke and Whited (2008), we examine how financing frictions affect real economic outcomes. But whereas their paper looks at corporate operating decisions, like 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 there are important differences: we perform our study at the *county* level, which represents an intermediate setting between the country level and firm level tests other papers employ and 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, rather than estimated measures such as total factor productivity.

The rest of the paper is organized as follows. Section 2 includes 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 its basic properties. Section 5 describes our methods for testing the relation between access to finance and productivity, and gives results. Section 6 discusses robustness tests for these results, and Section 7 concludes.

2. Literature and institutional detail

2.1. Background literature on the finance-growth nexus

Levine (2004) provides an in-depth review of the massive literature on the finance-growth nexus. What differentiates our paper from the rest of the literature is our empirical design: our natural experiment setting allows us to cleanly establish the direction of causality (finance causes growth), and we do so in a highly developed economy. In this subsection, we mention a few papers most relevant to our study.

Recent theoretical research has focused on the link between access to financing and productivity. For example, Levine (1991) demonstrates that stock markets fuel growth in two ways: by facilitating firm ownership transfers without disturbing production, and by permitting portfolio diversification. Bencivenga, Smith, and Starr (1995) develop a theory explaining how the financial sector can alleviate information transaction costs, which increases the viability of longer-gestation, higher-return projects.

A number of empirical studies examine the link between access to credit and productivity at the country level. Easterly and Levine (2001) find that total factor productivity drives a substantial portion of variation in cross-country differences in the level or growth rate of GDP per capita. Levine and Zervos (1998) argue that "stock market liquidity and banking development both positively predict growth, capital accumulation, and productivity improvements when entered together in regressions, even after controlling for economic and political factors" (pg. 537). In some cases, however, access to credit can have adverse effects on economic growth if capital is inefficiently allocated. Ghani and Suri (1999) argue that Malaysia's banking sector inefficiently allocated capital during the East Asian financial crisis, which led to a decline of the country's total factor productivity.

Other empirical studies, such as those of Bernstein and Nadiri (1993), Nickell and Nicholitsas (1999), Schiantarelli and Sembenelli (1999), Schiantarelli and Jaramillo (1999), and Schiantarelli and Srivastava (1999), find positive links between access to credit and productivity at the firm level. These studies are limited, however, because they focus on the effects of leverage on productivity. A recent paper by Gatti and Love (2006) addresses this shortcoming by using the presence or absence of overdrafts, and lines of credit as more direct measures of access to credit. Gatti and Love (2006) find that access to credit is positively associated with total factor productivity in their sample of Bulgarian firms.

2.2. Institutional detail: agricultural commodities

Agricultural spot markets are commodities markets in which agricultural goods are sold for cash and delivered without delay. Contracts bought and sold on these markets become effective immediately upon their transaction. Contract sizes are standardized and are typically in the thousands of bushels. Bushel sizes vary somewhat by crop, but are typically around fifty harvested pounds of a given crop.

2.3. Institutional detail: corn and soybeans

Corn, soybeans, and other crops are bought and sold on midwestern U.S. 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.

[Insert Table 1 here.]

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.

2.4. Institutional detail: ethanol

According to a recent 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.[1] 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), which had been a popular fuel additive. 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 U.S. gasoline manufacturers under the current federal tax law. Imported ethanol, on the other hand, faces a tariff of 54 cents per gallon (with the exception of duty-free status for

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

certain Central American and Caribbean countries on up to 7 percent of the U.S. market for imported ethanol). See Hahn (2008) for additional discussion of economic and political issues affecting ethanol production.

3. Analytical framework

In this section we propose a simple analytical framework to formalize the intuition for our empirical tests. Note that this setup is intended solely to motivate the empirical specification to come. It is not intended as a rigorously specified model. Consider a producer in a two-period world (t and t+1). The producer's problem is to maximize production in period t, subject to a budget constraint. We reference a Cobb-Douglas production function to represent the relation between inputs and outputs.

$$\max\ \Pi_t = aK_t^{\alpha} l_t^{\beta} L_t^{1-\alpha-\beta} \tag{1}$$

$$\text{s.t. } w_{K,t}K_t + w_{l,t}l_t + w_{L,t}L_t \le B_t \tag{2}$$

where

Π_t = Production at time t,

K_t = Capital at time t,

l_t = Land at time t,

L_t = Labor at time t,

a, α, β = Constants determined by technology,

$w_{K,t}$, $w_{l,t}$, $w_{L,t}$ = Respective prices of capital, land, and labor at time t,

B_t = Budget at time t, determined as follows

$$B_t = C_t + \delta PV(\Pi_{t+1}) \tag{3}$$

where

C_t = Cash on hand at time t,

δ = A measure of ability to borrow against future cash flows, and

$PV(\Pi_{t+1})$ = Present value of future production.

Our analysis focuses on the relation between the budget at time t, B_t, and the product of ability to borrow against future cash flows δ and the present value of future production $PV(\Pi_{t+1})$. A producer's budget increases with bank deposits in this framework. Producers can take advantage of this increase to enhance productivity. 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). 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 will be 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, $PV(\Pi_{t+1})$, and that the ability to borrow against these future cash flows varies cross-sectionally county-by-county depending on the accessibility of finance, δ. 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 budget for increased capital expenditures, for labor costs, or to buy more land—we can test the idea that the availability of external finance might 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 comprise county-level variables from the twelve states of the midwestern United States—Kansas, Illinois, Indiana, Iowa, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin—from 2000 to 2006. According to our calculations from USDA data, these twelve states comprise about 88 percent of all U.S. 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. We note that 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's (FDIC) website. 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. Our baseline measure of access to finance is a poor-finance county 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. We discuss the economic reasons for using this measure in more detail below.

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

[Insert Figure 1 here.]

4.2. Dependent variables

Our primary dependent variable is crop yield, measured in bushels per acre, which proxies for productivity. Crop yields data come from the National Agricultural Statistics Service (NASS), which is affiliated with the United States Department of Agriculture (USDA). Figures 2 and 3 show the changes of concentrations of corn and soybeans yields across the midwestern United States from 2000 to 2006. We give more detail as to the appropriateness of these crops in the Methods section below.

[Insert Figure 2 here.]

[Insert Figure 3 here.]

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's (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.

Figure 4 shows a map of ethanol plants and their production capacity as of 2006 plotted over county-level changes in corn yields. 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 may 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. We examine the location choice for ethanol production plants in the robustness section.

[Insert Figure 4 here.]

Not surprisingly, temperature and precipitation play an important role in the production of corn and soybeans (see Thompson (1986) and 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 I 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 follows:

$$GDD = \sum_{d=1}^{D} \max\left\{ \frac{T_{\max,d} + T_{\min,d}}{2} - T_{base}, 0 \right\} \tag{4}$$

where

D = Total number of days from May 1 through October 31,

$T_{max,d}$ = Maximum temperature for a given day, measured in degrees Fahrenheit,

$T_{min,d}$ = Minimum temperature for a given day, measured in degrees Fahrenheit,

and T_{base} = 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 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 assumption because the midwestern states exhibit little variation in topography and geology, especially within each state.[2]

We control for population density, because it may be related to deposits (urban areas are likely to have more financial institutions). Population density may also directly correlate with crop yields; for example, counties with higher levels of urbanization may be less suitable for agricultural growth (due to poorer air quality or less arable land) or because when population density increases, residents will urbanize land less suitable for agriculture, increasing yields per planted acre. We use the U.S. 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. 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 may be correlated. We explore this possibility in the robustness section.

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.

[Insert Table 2 here.]

[Insert Table 3 here.]

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

5. Methods and Results

5.1. Differences-in-differences-in-differences

We sort crop yields into thirty-five groups. First, we split the sample by year into seven groups (i.e., the data 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 4 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.

[Insert Table 4 here.]

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 Figure 5.

[Insert Figure 5 here.]

Table 4 shows an interesting feature of the relationship 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 will 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; we discuss below the results based on each of these measures.

5.2. Regression specification

We perform multivariate ordinary least squares (OLS) regressions. Equation (5) shows our basic regression approach. Subscripts *i*, *t*, and *k* denote county, year, and crop, respectively.

$$\begin{aligned} \text{Yield}_{i,t,k} = {} & \beta_1 \text{ Corn Dummy}_k \cdot \text{Access to Finance}_{i,t} \cdot \text{Ethanol Period}_t + \\ & \beta_2 \text{ Corn Dummy}_k \cdot \text{Access to Finance}_{i,t} + \\ & \beta_3 \text{ Corn Dummy}_k \cdot \text{Ethanol Period}_t + \\ & \beta_4 \text{ Corn Dummy}_k + \\ & \beta_5 \text{ Access to Finance}_{i,t} \cdot \text{Ethanol Period}_t + \\ & \beta_6 \text{ Access to Finance}_{i,t} + \\ & \beta_7 \text{ Ethanol Period}_t + \text{Controls} + \text{Constant} + \varepsilon_{i,t,k} \end{aligned} \tag{5}$$

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 control for time varying mean effects with our agricultural control (soybeans). We also use other measures to control for systemic time variation in productivity; we discuss these in the Robustness section below.

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 we note that 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 natural logarithm of inches of precipitation, and the natural logarithm of growing degree days. (We note that 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 may be nonlinear and/or non-monotonic—e.g., warm weather or precipitation may 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 we note that our main results do not change if we include them.

5.3. Regression results for corn and for soybeans

Our main results appear in Tables 5 and 6. In Table 5 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 weather and population 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, and/or time series variation within a state or county. Including county-fixed effects forces identification of the regression coefficients solely through time-series variation within a county. Standard errors are robust to heteroskedasticity, and we cluster them at the county level.

[Insert Table 5 here.]

Table 5 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. In the corn yield regression, the coefficient on the interaction between low-quintile deposits and ethanol is –4.0. 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 0.6 bushel differential response to the ethanol boom for counties with relatively good access to finance compared to those with poor access to finance. A visual inspection of these two magnitudes suggests that the effect on corn is much larger; we test this interpretation formally in the following analysis.

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 there may be some economies of scope 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 may have spillover effects to several crops if the equipment is not too specialized.

5.4. Pooled regression results

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, and 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.

[Insert Table 6 here.]

Table 6 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 –2.4, 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.

We note that 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 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 –2.7 bushels per acre, which is greater than 10 percent 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, rather than discrete, measure. We expect this variable to have a positive relation with productivity. Productivity may 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 will be 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

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 may be endogenous with crop yields due to economic prosperity. That is, if a county experiences high crop yields, this will lead to more wealth for the farmers in the county, who may 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 may 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 (4) in Table 6 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 0.9, which means that a one-standard deviation increase in the logged number of county-level bank branches explains nearly 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 above that in the short run the number of bank branches should be insensitive to changes in crop yields, and therefore 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 may 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 section.

We reproduce the results displayed in Panel A of Table 5 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*$_t$ · *Ethanol Period* and *Low Deposits*$_{t\text{-}k}$ · *Ethanol Period*; *Low Deposits*$_t$ and *Low Deposits*$_{t\text{-}k}$; *Ln Branches*$_t$ · *Ethanol Period* and *Ln Branches*$_{t\text{-}k}$ · *Ethanol Period*; and *Ln Branches*$_t$ and *Ln Branches*$_{t\text{-}k}$ 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 only affect productivity inasmuch as they affect access to finance in the current year.

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.

In addition to the methods described above, we explore—and ultimately reject— the possibility of using as an instrument for access to finance the county-level fraction of senior citizens. Becker (2007) documents the intuitive result that metropolitan statistical areas (MSAs) with a large fraction of seniors have higher local volumes of bank deposits. But we find the opposite for our sample of mostly rural Midwestern counties. (We note that when we condition on county population we find, as Becker (2007) does, a positive relation between fraction of seniors and deposits.) We offer two possible explanations for this discrepancy. First, in rural areas, young people may depart economically stagnant areas for urban areas with more job prospects. Such a migration may leave economically disadvantaged counties—counties that are likely to have low levels of bank deposits—with high levels of seniors. In MSAs, the flight of youth may be less prevalent, and so the fact that seniors keep more of their wealth in deposits may have the dominant effect. A second explanation consistent with our finding is as follows. As citizens in rural counties age, only those with sufficiently high net worth may be able to move from their rural residences to retire in urban counties, thus leaving behind the relatively poor seniors who hold low levels of bank deposits. The urban counties with a high concentration of relatively wealthy seniors will have high levels of bank deposits, while the rural counties with a high concentration of seniors (that is, seniors who lack the funds to move to retirement communities in urban areas and thus have low wealth) will necessarily hold low levels of bank deposits.

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 one percent 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, may not be a reasonable measure of access to finance if financial capital is geographically mobile. County-level bank deposits may be capturing a wider, regional effect of access to finance, or maybe capital markets 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. (We note that using the average, rather than sum, of contiguous county deposits, or using the level of deposits rather than 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 7 presents the results.

[Insert Table 7 here.]

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 may 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 8 presents the regression results.

[Insert Table 8 here.]

The relation in the baseline regressions—namely, that poor access to finance relates negatively to productivity—continues to hold. Specifically, we see that about 3,000 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 (1996) 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 Jayaratne and Strahan's (1996) starting date, 1972, and extend the sample through 2002 (Jayaratne and Strahan's (1996) 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 U.S. 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 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 U.S. corn. Standard errors are robust to heteroskedasticity and clustered at the state level, our unit of observation for these tests. Table 9 presents the results.

[Insert Table 9 here.]

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

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

So far we have documented 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 10 presents the regression results.

[Insert Table 10 here.]

We find a significant relation between ethanol production capacity and access to finance. In all four of our regression specifications we find a significant and negative effect of poor access to finance on ethanol plant location or size. (We note that we find similar results when we use the number of county-level bank branches as the explanatory variable, rather than 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 and/or capacity of ethanol production plants could be endogenous—plants' location and/or size could be chosen based on where there is good access to finance, or finance could follow to the areas where there are ethanol plants. 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 $\textit{Low Deposits}_{2004}$ and $\textit{Low Deposits}_{2006}$; and $\textit{Ln Branches}_{2004}$ and $\textit{Ln Branches}_{2006}$ 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 only affect 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 1.3 million gallons of ethanol production capacity in each of the following years. (The regression coefficient is 0.284, and $e^{0.284}$ is about 1.3.) 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 0.175, and $e^{0.175}$ 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. Indeed, a visual inspection of a time series of crop prices plotted in Figure 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.[3] 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

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

given year. This variable enters our multivariate regressions. Figure 6 displays spot market prices over time.

[Insert Figure 6 here.]

We use pricing data from spot markets in Illinois. (We note that 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.

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 run the baseline regressions from Table 5 separately on both subsamples. (Because the farm size measure imposes a large and possibly non-random 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 smaller firms (farms) are more sensitive to access to external finance than larger firms (farms). We note that other partitions—by quartile or decile, for instance—give the same results.

6.9. Alternative productivity controls

Our baseline regressions in Table 6 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 indeed 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 U.S. behind corn). Data on labor productivity come from the Bureau of Labor Statistics (BLS), 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 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 5, 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.

7. Conclusion

This paper examines the effect of access to finance on productivity. We exploit an exogenous shift in demand for U.S. 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 to 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 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 2.4 to 2.7 bushels per acre lower in counties with bank deposits in the lowest quintile during the ethanol boom period. This magnitude is greater than 10 percent 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 document 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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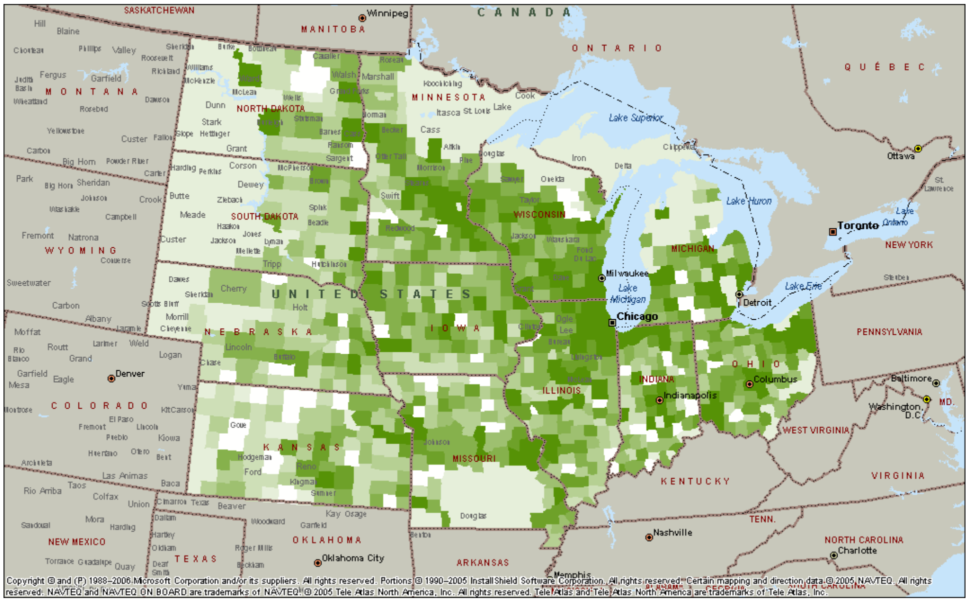

Fig. 1. Changes of county-level bank deposits. This figure shows the change of relative density of bank deposits within counties in the midwestern United States from 2000 to 2006. Darker shading indicates greater growth in bank deposits.

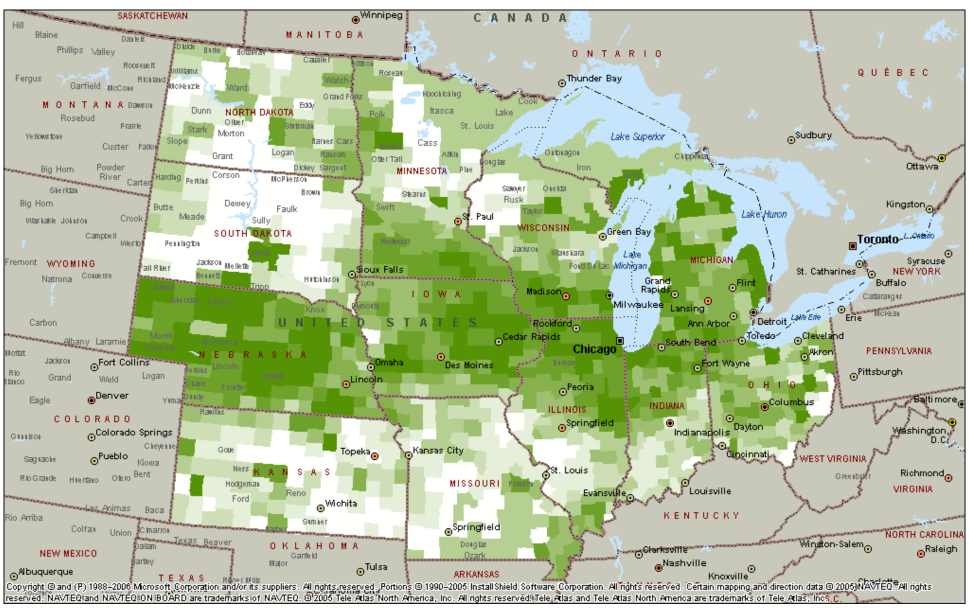

Fig. 2. Changes of county-level corn yields. This figure shows the change of relative density of corn yields produced by counties in the midwestern United States from 2000 to 2006. Darker shading indicates relatively greater growth in corn yields.

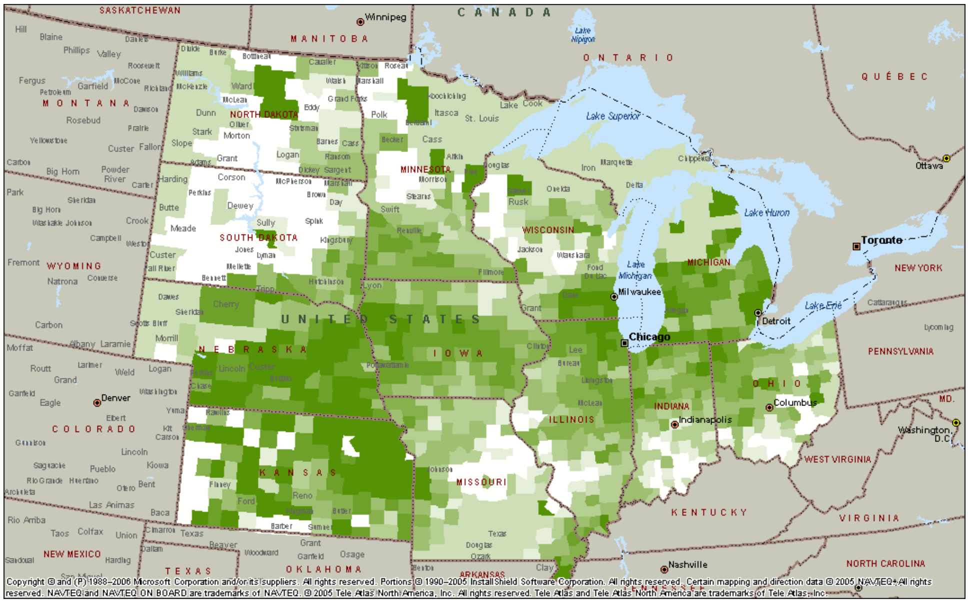

Fig. 3. Changes of county-level soybean yields. This figure shows the change of relative density of soybean yields produced by counties in the midwestern United States from 2000 to 2006. Darker shading indicates relatively greater growth in soybean yields.

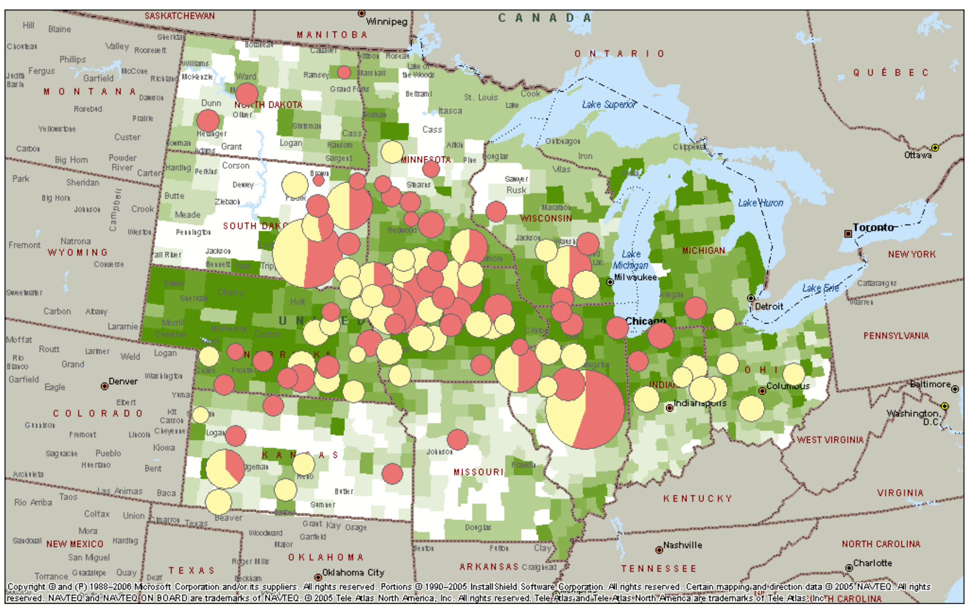

Fig. 4. Ethanol production capacity plotted over changes of corn yields. County-level ethanol production capacity data are represented by pie charts. Red slices represent in-place ethanol production capacity as of April 2006, and yellow slices represent ethanol production capacity planned for expansion. 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.

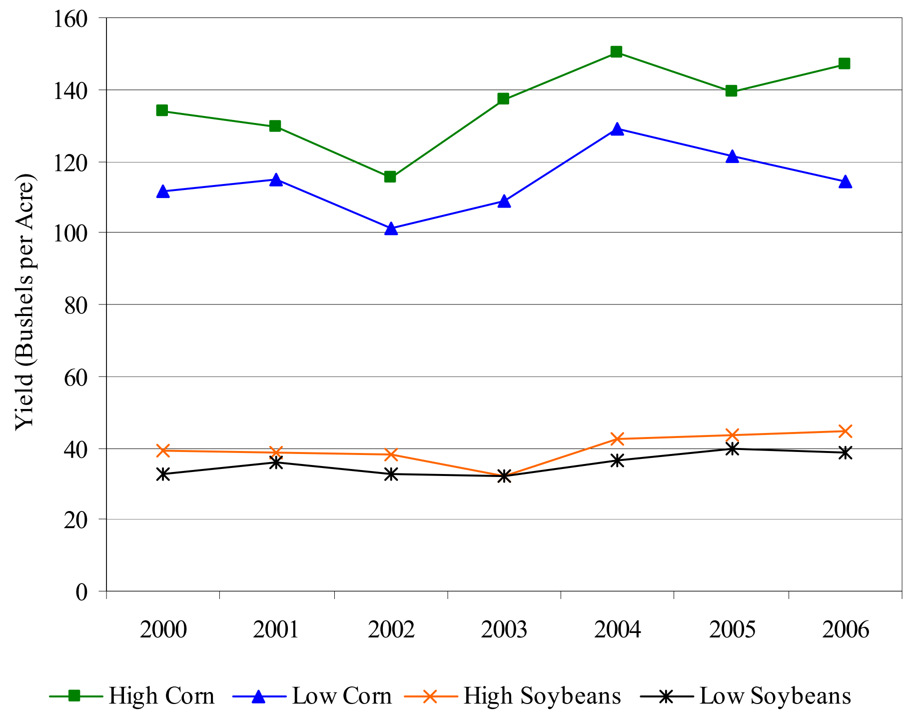

Fig. 5. Average corn and soybean yields in high and low bank deposit quintiles. This figure contains time-series plots of four variables measured annually from 2000 to 2006: (1) the average corn yield in counties with bank deposits in the highest quintile, (2) the average corn yield in counties with bank deposits in the lowest quintile, (3) the average soybean yield in counties with bank deposits in the highest quintile, and (4) the average soybean yield in counties with bank deposits in the lowest quintile.

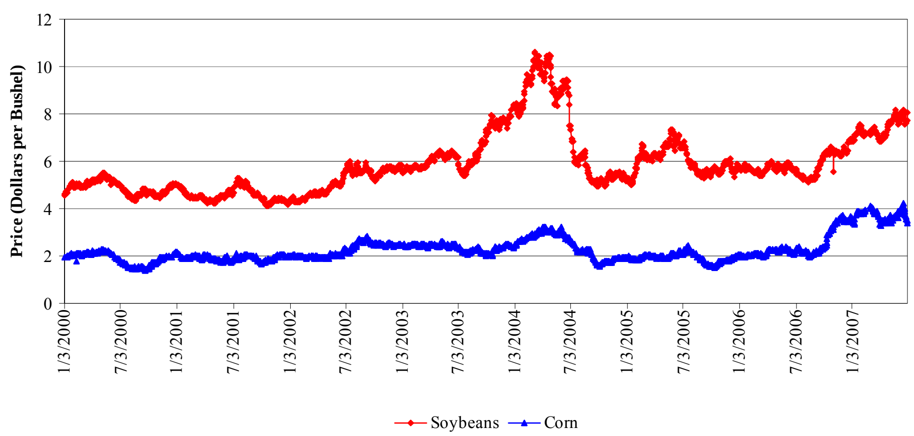

Fig. 6. Crop prices over time. This figure displays daily prices of yellow soybeans and yellow-kernelled corn sold on spot markets in Illinois from January 2000 to June 2007 in dollars per bushel.

Table 1
Crop Details

This table specifies the variety of each crop we study in the paper. This table also contains information quantifying recent U.S. harvests of each crop measured, and the time of year which each crop is planted and harvested. Harvest amounts, and planting and harvest seasons information come from the United States Department of Agriculture (USDA).

Crop	Variety	2002 Harvested Acres†	2007 Harvested Acres†	Planting Season	Harvest Season
Corn	Yellow-Kernelled (Field Corn)	68.2	85.4	Spring	Fall
Soybeans	Yellow	72.4	63.3	Late Spring	Fall

† Millions of acres

Table 2
Summary statistics

Panel A presents pooled summary statistics for county-year-crop observations. We examine counties in the twelve midwestern U.S. 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's (NASS) website, which is affiliated with the United States Department of Agriculture (USDA). *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. Deposits data come from the FDIC's website. *Price* represents the average spot market price of corn or soybeans during the harvest period. *Price* is measured in dollars per bushel, and is collected from Bloomberg. *Population Density* is equal to the county population for a given year divided by the number of square miles in the county. Population data come from the U.S. 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.

Panel A

	N	Mean	SD	Min	25%	Median	75%	Max
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	13,046	1,064	5,677	0.8	151	300	638	180,338
Branches	13,678	23.6	57.5	0	7	11	21	1,616
Price of Corn	6,723	1.99	0.35	1.64	1.65	1.82	2.34	2.62
Price of Soybeans	6,323	5.45	0.78	4.37	4.67	5.55	5.76	6.99
Pop. Density	12,918	261.3	1,242.7	0.9	29.0	72.2	175.1	32,789.8
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

	N	Mean	SD	Min	25%	Median	75%	Max
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

Table 3
Correlation Matrix

This table presents pairwise correlations of county-year observations. We examine all counties in the twelve midwestern U.S. 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's (NASS) website, which is affiliated with the United States Department of Agriculture (USDA). *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. *Price of Corn* and *Price of Soybeans* represent the average spot market prices of corn and soybeans during the harvest period. Prices are measured in dollars per bushel, and are collected from Bloomberg. *Population Density* is equal to the county population for a given year divided by the number of square miles in the county. Population data come from the U.S. 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 ten percent, five percent, and one percent levels, respectively.

	GDD	Corn Yield	Soybeans Yield	Deposits	Branches	Price of Corn	Price of Soybeans	Population Density
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***				
Price of Corn	0.106***	–0.069***	–0.012	0.012	0.008			
Price of Soybeans	0.084***	–0.006	–0.136***	0.013	0.008	0.485***		
Population Density	0.010	0.017	0.003	0.507***	0.586***	0.003	0.003	
Precip.	0.097***	0.082***	0.101***	–0.021*	–0.016	–0.007	–0.063***	0.008

Table 4
Univariate tests of corn and soybean yields using a two-way sort

Each cell of the grid below 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 ten percent, five percent, and one percent levels, respectively.

	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**

Table 5
Individual regressions for crn and soybeans

This table presents OLS 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. *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 ten percent, five percent, and one percent levels, respectively.

Panel A – Determinants of corn yields

	(1)	(2)	(3)
Low Deposits · Ethanol Period	–3.595**	–4.046***	–6.145***
	(1.590)	(1.474)	(1.482)
Low Deposits	–6.802**	–0.381	1.937
	(2.758)	(2.251)	(2.444)
Ethanol Period	6.766***	7.535***	9.116***
	(0.670)	(0.626)	(0.648)
Ethanol County	14.708***	9.578***	–
	(2.455)	(2.004)	(–)
Ln Population Density	3.894***	1.584**	–7.445
	(0.733)	(0.655)	(12.398)
Ln Precipitation	7.045***	1.984**	11.273***
	(1.211)	(0.998)	(0.717)
Ln GDD	6.132	–1.963	–18.818***
	(3.927)	(3.677)	(3.241)
Constant	42.029	130.446***	274.278***
	(30.849)	(29.006)	(57.072)
N	6,608	6,608	6,608
Adjusted R^2	0.113	0.344	0.650
State Dummies?	No	Yes	No
County Fixed Effects?	No	No	Yes

Panel B – Determinants of soybeans yields

	(1)	(2)	(3)
Low Deposits · Ethanol Period	–0.656	–0.642	–1.514***
	(0.532)	(0.490)	(0.454)
Low Deposits	–1.309	–0.043	1.908**
	(0.812)	(0.630)	(0.829)
Ethanol Period	4.947***	4.925***	5.249***
	(0.214)	(0.194)	(0.195)
Ethanol County	3.971***	2.544***	–
	(0.671)	(0.506)	(–)
Ln Population Density	0.983***	–0.089	–4.674
	(0.224)	(0.180)	(3.890)
Ln Precipitation	2.291***	0.618**	3.511***
	(0.340)	(0.285)	(0.223)
Ln GDD	2.559**	2.637**	0.497
	(1.287)	(1.053)	(0.811)
Constant	5.677	14.802*	42.671**
	(9.813)	(8.290)	(17.957)
N	6,241	6,241	6,241
Adjusted R^2	0.126	0.390	0.614
State Dummies?	No	Yes	No
County Fixed Effects?	No	No	Yes

Table 6

Pooled regressions for corn and soybeans

This table presents pooled OLS regression results based on county-year-crop observations. The regressions specification is $Yield_{i,t,k} = \beta_1\ Corn_k \cdot Access\ to\ Finance_{i,t} \cdot Ethanol\ Period_t + \beta_2\ Corn_k \cdot Access\ to\ Finance_{i,t} + \beta_3\ Corn_k \cdot Ethanol\ Period_t + \beta_4\ Corn_k + \beta_5\ Access\ to\ Finance_{i,t} \cdot Ethanol\ Period_t + \beta_6\ Access\ to\ Finance_{i,t} + \beta_7\ Ethanol\ Period_t + Controls + Constant + \varepsilon_{i,t,k}$. The dependent variable is crop yield, measured in bushels per acre. We separately winsorize corn and soybean yields at one percent. 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. Population data come from the U.S. 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. The standard errors are in parentheses. They are robust to heteroskedasticity, and we cluster them at the county level. *, **, and *** represent significance at the ten percent, five percent, and one percent levels, respectively.

Finance is measured by:	Low deposits dummy			Ln(Deposits)	Ln(Number of bank branches)
	(1)	(2)	(3)	(4)	(5)
Corn · Finance · Ethanol Period	-2.450*	–2.654**	–2.368*	0.682	0.943**
	(1.368)	(1.339)	(1.437)	(0.480)	(0.460)
Corn · Finance	-13.791***	–13.616***	–12.829***	5.144***	4.349***
	(1.898)	(1.865)	(1.886)	(0.703)	(0.698)
Corn · Ethanol Period	2.105***	2.097***	1.961***	1.273***	1.657***
	(0.481)	(0.473)	(0.492)	(0.450)	(0.433)
Corn	94.569***	94.715***	95.497***	91.939***	91.931***
	(0.665)	(0.658)	(0.666)	(0.657)	(0.649)
Finance · Ethanol Period	-0.956*	–1.052**	–2.844***	0.594***	0.528***
	(0.522)	(0.493)	(0.696)	(0.173)	(0.159)
Finance	2.916**	6.825***	8.834***	–1.235	–2.482**
	(1.252)	(1.239)	(1.865)	(0.311)	(1.089)
Ethanol Period	4.766***	5.169***	6.308***	4.991***	4.934***
	(0.309)	(0.277)	(0.270)	(0.278)	(0.265)
Ethanol County	9.481***	6.139***	–	6.115***	6.229***
	(1.528)	(1.249)	(–)	(1.295)	(1.267)
Ln Population Density	2.526***	0.872**	–4.484	–0.124	0.997
	(0.472)	(0.415)	(7.293)	(0.970)	(0.869)
Ln Precipitation	4.879***	1.530**	7.596***	1.779***	1.567**
	(0.767)	(0.642)	(0.434)	(0.665)	(0.652)
Ln GDD	4.617*	0.344	–9.889***	0.712	0.328
	(2.577)	(2.365)	(1.898)	(0.766)	(2.353)
Constant	-26.712	23.931	109.085***	25.878	24.788
	(20.164)	(18.628)	(33.598)	(19.213)	(18.909)
N	12,849	12,849	12,849	12,849	12,849
Adjusted R^2	0.790	0.833	0.888	0.828	0.832
State Dummies?	No	Yes	No	Yes	Yes
County Fixed Effects?	No	No	Yes	No	No

Table 7
Regressions including deposits in contiguous counties

This table presents pooled OLS 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 one percent. 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. *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 ten percent, five percent, and one percent levels, respectively.

	(1)	(2)	(3)
Corn · Low Deposits · Ethanol Period	–2.600*	–2.870*	–2.745*
	(1.529)	(1.494)	(1.567)
Corn · Low Contiguous Deposits · Ethanol Period	–0.793	–0.440	–0.563
	(1.933)	(1.888)	(1.907)
Corn · Low Deposits	–12.867***	–12.722***	–11.317***
	(2.035)	(2.019)	(2.048)
Corn · Low Contiguous Deposits	–2.231	–2.319	–3.570**
	(1.657)	(1.654)	(1.644)
Corn · Ethanol Period	2.038***	1.992***	1.794***
	(0.502)	(0.497)	(519)
Corn	94.907***	95.062***	96.040***
	(0.690)	(0.684)	(0.688)
Ethanol Period	4.837***	5.129***	6.335***
	(0.312)	(0.279)	(0.284)
Low Deposits · Ethanol Period	–0.769	–1.185**	–2.777***
	(0.565)	(0.548)	(0.754)
Low Contiguous Deposits · Ethanol Period	0.110	0.525	0.588
	(0.686)	(0.652)	(0.810)
Low Deposits	2.389**	6.586***	8.177***
	(1.178)	(0.1.224)	(1.931)
Low Contiguous Deposits	1.319	0.014	1.177
	(0.816)	(0.872)	(1.135)
Ethanol County	9.478***	6.170***	–
	(1.519)	(1.242)	(–)
Ln Population Density	2.543***	0.789*	–3.421
	(0.498)	(0.428)	(7.317)
Ln Precipitation	4.893***	1.541**	7.571***
	(0.768)	(0.644)	(0.434)
Ln GDD	4.625*	0.274	–10.054***
	(2.573)	(2.373)	(1.908)
Constant	–27.103	24.841	105.745***
	(20.248)	(18.770)	(33.599)
N	12,849	12,849	12,849
Adjusted R^2	0.790	0.833	0.888
State Dummies?	No	Yes	No
County-Fixed Effects?	No	No	Yes

Table 8
Regressions with planted acreage proxying for productivity

This table presents pooled OLS regression results based on 12,849 county-year-crop observations. The regression specification is $Planted\ Acreage_{i,t,k} = \beta_1\ Corn_k \cdot Low\ Deposits_{i,t} \cdot Ethanol\ Period_t + \beta_2\ Corn_k \cdot Low\ Deposits_{i,t} + \beta_3\ Corn_k \cdot Ethanol\ Period_t + \beta_4\ Corn_k + \beta_5\ Low\ Deposits_{i,t} \cdot Ethanol\ Period_t + \beta_6\ Low\ Deposits_{i,t} + \beta_7\ Ethanol\ Period_t + Controls + Constant + \varepsilon_{i,t,k}$. 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. *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 ten percent, five percent, and one percent levels, respectively.

	(1)	(2)	(3)
Corn · Low Deposits · Ethanol Period	–2,747**	–3,017**	–3,227***
	(1,330)	(1,288)	(1,106)
Corn · Low Deposits	567	1,249	3,420
	(2,882)	(2,861)	(2,911)
Corn · Ethanol Period	3,587***	3,425***	3,311***
	(561)	(515)	(436)
Corn	412	941	2,758*
	(1,477)	(1,458)	(1,481)
Low Deposits · Ethanol Period	777	1,768	2,025**
	(1,446)	(1,387)	(913)
Low Deposits	–40,930***	–37,325***	–596
	(4,807)	(4,636)	(1,664)
Ethanol Period	153	–2,470***	–765**
	(813)	(868)	(382)
Ethanol County	44,562***	33,143***	–
	(5,309)	(4,558)	(–)
Ln Population Density	–5,573***	–3,325**	–23,693***
	(1,283)	(1,541)	(6,114)
Ln Precipitation	4,360**	1,883	–158
	(1,952)	(1,976)	(128)
Ln GDD	–9,385	17,069**	–1,693***
	(6,554)	(7,706)	(540)
Constant	155,286***	–55,482	181,836***
	(53,527)	(62,251)	(26,238)
N	12,849	12,849	12,849
Adjusted R^2	0.141	0.342	0.864
State Dummies?	No	Yes	No
County-Fixed Effects?	No	No	Yes

Table 9

Productivity regressions with bank branch deregulation and corn syrup

This table presents pooled OLS regression results based on 724 state-year-crop observations from 1972-2002. 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 ten percent, five percent, and one percent levels, respectively.

	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

Table 10

Ethanol production as a function of access to finance

Panel A presents regression results based on 925 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 OLS 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. *Cord 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 917 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. *Cord 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. *, **, and *** represent significance at the ten percent, five percent, and one percent levels, respectively.

Panel A – Ethanol regressed on low deposits dummy variable

Dependent variable is:	Ethanol county dummy	Ln(Production capacity in place)	Ln(Planned capacity)	Ln(Planned plus in-place capacity)
	(1)	(2)	(3)	(4)
Low Deposits	–0.785***	–0.280***	–0.224**	–0.486***
	(0.213)	(0.105)	(0.110)	(0.141)
Corn Yield$_{t-1}$	0.011***	0.004***	0.005***	0.008***
	(0.002)	(0.001)	(0.001)	(0.001)
Population Density	–0.133***	–0.057***	–0.045***	–0.097***
	(0.049)	(0.027)	(0.029)	(0.037)
Constant	–2.07***	0.024	–0.183	–0.100
	(0.374)	(0.191)	(0.199)	(0.255)
N	925	925	925	925
Pseudo- or Adjusted R^2	0.084	0.024	0.028	0.051

Panel B – Future ethanol production capacity regressed on instrumented access to finance

	(1)	(2)
Instrumented Low Deposits Dummy	–0.284**	
	(0.125)	
Instrumented Ln(Number of Bank Branches)		0.175**
		(0.076)
Corn Yield$_{t-1}$	0.005***	0.005***
	(0.001)	(0.001)
Population Density	–0.054*	–0.114**
	(0.031)	(0.051)
Constant	–0.119	0.026
	(0.211)	(0.254)
N	917	917
Adjusted R^2	0.027	0.029