Household Inequality, Corporate Capital Structure and Entrepreneurial Dynamism

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Abstract

We empirically test hypotheses emanating from recent theory predicting that household wealth inequality may determine corporate financing and entrepreneurial dynamism. We construct two measures of wealth inequality at the US county level: one based on the distribution of financial rents in 2004 and another related to the distribution of land holdings in the late Nineteenth century. Our results suggests that entrepreneurs located in more unequal counties are more likely to finance their venture with their own resources or via bank and family financing. At the same time, they are less likely to use equity from angels and venture capital and to work in high-tech sectors. In financial markets, wealth inequality may affect capital structure/entrepreneurial choices both via demand and supply: we find evidence in favor of both channels.

Keywords: inequality, corporate financing, entrepreneurship.

JEL: D31, G3, L26.

I. Introduction

Households' wealth inequality is a defining societal characteristic with important implications for economics and finance. Already in the Wealth of Nations, Adam Smith expressed concerns that an unequal distribution of the land may have had a negative impact on the development of the New World colonies. In his words "*The engrossing of land, in effect, destroys this plenty and cheapness*".[1]

The growth of Wealth Inequality during recent decades have brought the issue back to the top of the agenda of policymakers and social leaders in many Western economies. While recent academic work has consequently revisited its defining, measuring, and analysing (Chetty, Hendren, Kline and Saez (2014); Chetty, Hendren, Kline, Saez and Turner (2014); Piketty (2014)), policymaker and academic interest has also turned to the possible social and economic consequences of inequality.

This paper sheds light on the economic consequences of households' wealth inequality, and in particular studies the links between wealth inequality and the financing and production/technology choices of young entrepreneurs. This is an important question as the type of productions, as well as the predominant means for financing them, are defining features of any economic system and they are likely to have an important impact on economic development.

Recent economic theory directly links the degree of wealth inequality to economic and financial outcomes. Engerman and Sokoloff (1997) and Engerman and Sokoloff (2002) describe how large levels of wealth inequality could impair the development of institutions that are conducive for economic growth. In unequal societies wealthy elites may prevent the sound development of basic institutions such as schools, the judiciary and capital markets, in

[1] Wealth of Nations, IV.7.41, p. 726.

order to maintain their grip on power. According to this view, an unequal society will be characterized by less effective schooling and law enforcement and by a poorly-developed financial system. And Perotti and von Thadden (2006) build a model in which the median voter in an unequal society only owns her non-diversifiable human capital. As a result, she may prefer a financial system dominated by family and bank, "institutions" with whom she shares her aversion to risk. In more equal societies, the median voter may also own diversifiable financial wealth, and may prefer a system that also relies on equity financing and is characterized by risk-taking dynamism (see also Rajan and Ramcharan (2011)).

All in all, these theories predict how wealth inequality may affect financing and technology choices of firms. In more unequal societies, either because of a lack of higher education or because of poorly-developed financial markets, firms are more likely to operate in traditional sectors, come with a simpler corporate form and rely on internal sources of funding. In more unequal societies, bank debt or family loans, as opposed to equity from institutional investors, will be the prevailing form of external finance.

This study will focus on households' wealth inequality measured at the US County level and relate it to the choices of firms located in the same area. Even if many of the political decisions are taken at the state level, counties are in effect co-responsible for many important elements of public life, such as the organization of schooling, the judiciary, the enforcement of the law, and taxation.[2] Focusing on the local county level substantially "shortens the distance" between the local institutional conditions and the corporate outcomes and therefore allows us to obtain more precise estimates of the effects of interest. We will also study start-

[2] Ramcharan (2010), Rajan and Ramcharan (2011), Vollrath (2006; 2013) also relate county level inequality to various economic outcomes such as income redistribution, access to credit and schooling.

up firms: First, their financing is more likely to depend upon local credit market conditions (Lerner (1995); Sorenson and Stuart (2001); Petersen and Rajan (2002); Guiso, Sapienza and Zingales (2004); Chen, Gompers, Kovner and Lerner (2010); Berger, Cerqueiro and Penas (2014)); second, it allows us to more precisely identify entrepreneurial dynamics, as we can observe technology and production choices at the very beginning of the firm's life cycle.

Identifying the effect of inequality on corporate outcomes presents us with steep empirical challenges. First, it is difficult to measure wealth inequality at a local level because direct and reliable households wealth data at a county level is virtually impossible to find. Second, corporate outcomes themselves (such as the local ease to start a *de novo* firm and the resultant distribution of profits) could easily determine local wealth inequality at the household level.

We address the first problem by constructing two proxies of wealth inequality: One based on contemporary sources and another one that relies on historical records. The present-day measure of wealth inequality is based on the amounts of dividends and interests earned by US households in 2004, as reported by Internal Revenue Service (IRS) Statistics of Income (IRS-SOI) data. The IRS-SOI data report the total amount of dividends and interest income received by US households in each postal zip code. Under the assumption that a typical household holds the market index for stocks and bonds, the amount of financial rents it receives depends only on the quantity of stocks and bonds it holds, in other words, by the total amount of financial wealth it owns. For each zip code, the IRS provides this information for five income groups. It also reports the number of households belonging to each income group and the total amount of interests and dividends earned by each income group. We use this information to construct the distribution of financial rents by zip code, then we aggregate it at

the county level and compute a county Gini coefficient of financial wealth inequality (*à la* Mian, Rao and Sufi (2013)).

The historical measure of wealth inequality is the distribution of land holdings at the US county level in 1890 (*sic*), a measure which given its historic nature is strappingly pre-determined. To construct the Gini-coefficient of land holdings in 1890, we access the US Census of Agriculture dataset that contains the size and number of farms in all counties recorded every ten years since 1860 (due to missing observations for counties in Oklahoma the state-level coefficient has to be used). Such a measure has already been employed by Galor, Moav and Vollrath (2009), Ramcharan (2010), Rajan and Ramcharan (2011) and Vollrath (2013) for example to study US historical developments in education, banking and redistribution.

For our historical measure to be able to deliver it has to be true that counties with a more unequal land distribution in 1890 are also those that are characterized by a higher wealth inequality today. We validate this measure by checking its correlation with factors (also measured at county level) that arguably are related to the degree of wealth inequality. We find that 1890 land inequality displays a 36 and 46 percent positive correlation with our 2004 measures of dividend and interest inequality, for example. It is also positively correlated with the local poverty rates (43 percent) and the number of crimes per capita (33 percent) and it is negatively correlated with the number of white people living in a county (-53 percent).[3]

[3] We assume here that the share of white people represents fairly well the proportion of the middle class living in a county. We take the data on poverty rates from the US Census bureau. These figures do not define poverty only based on income factors, but also to factors more related with wealth, such as the amount of money held in deposit accounts and the participation to various food/meal assistance programs.

The second empirical challenge consists of precisely identifying a causal relationship between wealth inequality and corporate outcomes. In this respect the timing of our historical proxy alleviates concerns related to reverse causality. Yet, wealth inequality itself may be correlated with unobserved factors likely to affect our estimates. We tackle this problem in various ways. First, as our measures of wealth inequality are at the county level (and since we know the precise location of the firms) we load our specifications with state, year, industry, state-year and/or industry-year fixed effects to account for any unobserved heterogeneity at those aforementioned levels. This allows us to take into account changes in, for instance, legislation and regulation at the State level as well as their legal traditions and type of colonization. We further control for a large number of salient firm, main owner taken from the Kauffmann Survey of Business Formation database which is also used to construct our main dependent outcome variables of interest. Additionally, our regressions also include various measures of county demographic and socio-economic characteristics.

Second, following the literature (Easterly (2007); Galor, Moav and Vollrath (2009); Ramcharan (2010); Rajan and Ramcharan (2011)), we instrument the contemporary measure of wealth inequality with a set of variables related to the historical averages of rainfall and temperature (at the district level) that have been considered an exogenous predictor of contemporary wealth inequality.[4] We consider this a valid strategy, in light of the historical evidence provided by Engerman and Sokoloff (2002) that the quality of soil combined with the climate may have a persistent effect on the degree of inequality. In particular, regions whose soil and climate are best suited for large farms, like cotton or tobacco, should induce

[4] A district is defined by the National Climatic Data Center as a cluster of two or three counties sharing similar climatic conditions.

relatively high wealth inequality. The production of these crops entails high fixed costs. As a result, the market, in equilibrium, can support only a few farms owned by a few wealthy individuals. Under this perspective, the observed rainfall and temperature are good predictors of wealth inequality to the extent that inequality and institutions persist throughout time.[5] Engerman and Sokoloff (1997), Engerman and Sokoloff (2002) and Rajan (2009) suggest that this is the case and, ultimately, this is an empirical question that our first stage regressions will address.

Even after saturating specifications with the aforementioned dense sets of fixed effects and characteristics, the estimated coefficients robustly suggest that county-level wealth inequality increases the likelihood that a firm is a sole-proprietorship and boosts its proportion of inside equity, family and bank financing (the latter to both owner or firm). Angel and venture capital financing on the other hand decreases in inequality, and so does the likelihood that newly created firms are high-tech. Important for our identification strategy, we also notice that including controls in our regressions, leaves the relationship between wealth inequality and entrepreneurial outcomes unaltered or, if any, make it stronger rather than weaker. To the extent that firms and state/county unobservable characteristics are correlated to our controls, it appears that endogeneity works against finding any link between wealth inequality, start-up capital structure and technology choices (Altonji, Elder and Taber (2005); Bellows and Miguel (2006); Bellows and Miguel (2009)).

Our estimates are not only statistically significant, but also economically relevant. A one standard deviation increase in county-level wealth inequality for example increases the

[5] We do not instrument the historical proxy of inequality because the rainfall and temperature data we have access to are averages for the Twentieth century and consequently follow our 1890 measure of land distribution in time.

likelihood of a sole proprietorship is locally present by 13 percent (of its own mean). Similarly constructed semi-elasticities for the effect of inequality on internal equity and family and bank financing 13 and 30 percent, respectively. The likelihood that newly created firms are high-tech is lower by around 8 percent in more unequal counties.

Our analysis identifies a reduced-form relationship between wealth inequality, capital structure and firms' technology choices: in the financial markets, such a relationship could be mediated both by supply and demand factors. On the supply side, wealth inequality may result into inefficient financial markets and restrictions to the supply of external finance. On the demand side inequality could be associated with a lower demand for external finance because, for instance, of the entrepreneurs' education level. To the extent that in unequal counties education is poorer, less educated entrepreneurs may choose to work in low-tech ventures which may require either own- or bank-financing.

We evaluate the relevance of both supply and demand factors, and we consider in particular the restrictions in credit supply and the relative importance of education. We find results that lend support to both supply and demand factors: In unequal counties there are a lower number of bank establishments per capita, which suggests that entrepreneurs may be rationed on the credit market.[6] Unequal counties also have a lower percentage of the population with at least college degree and they are less likely to attract educated people from other geographical areas.

In the last step of our study, we provide some suggestive evidence that evaluates the median voter mechanism suggested by Perotti and von Thadden (2006). Recall that their

[6]We follow Rajan and Ramcharan (2011) and use the number of bank establishments per capita as proxy of the supply of debt finance.

model links inequality to finance via a supply-side explanation: Citizens decide who will be the main supplier of finance in their area. Together with the degree of wealth inequality, a key ingredient in their model is that agents are called to vote on the precise financial system they prefer (bank versus equity). As our geographical unit of analysis is the US county, we look at a county-level institution that (at least in many US States) citizens vote on, i.e., judges of the first-degree courts. In particular, we examine whether, in more unequal counties, the decisions of judges in civil cases are more likely to favour banks over businesses (or broadly speaking equity). Judges` decisions to "favour" banks in trials may reflect the general preferences of the population or the ability of the banks to lobby the judiciary, for instance by financing the electoral campaigns of judges.[7] The latter case would be in the spirit of the Engerman and Sokoloff (2002) as it would indicate that banks are part of or captured by the wealthy elites and are capable to indirectly affect judiciary decisions. If this is the case, we would expect judges' decisions to be more likely to favour a bank when judges are less independent, for instance when they stay in office for a shorter period of time before facing re-elections.

We find some limited evidence for the latter explanation. Indeed while we do not find any relationship between county wealth inequality and first-degree judges' decisions, we do find that in counties where judges are elected or are appointed for a shorter term in office there is a positive relationship between local wealth inequality and the probability that a judge, everything else equal, will rule in favour of a bank. Similarly, in counties where the judiciary is elected via Partisan elections (and electoral contributions may play a bigger role) there is a positive relationship between wealth inequality and rulings in favour of banks.

[7] On the history, theory and measuring of judicial independence in the US, see Hanssen (2004b) and Hanssen (2004a).

In sum, our findings vividly demonstrate the importance of inequality for corporate outcomes, and not only contribute to the already-cited literature that specifically links wealth inequality with firm ownership, financing and entrepreneurial dynamism, but also contributes directly to our understanding of all relevant factors shaping such outcomes. In his Opus entitled "The Theory of Economic Development," Joseph Schumpeter stated that "an individual can only become an entrepreneur by previously becom[ing] a debtor" (Schumpeter (1934), p. 102).

While the Schumpeterian notion of creative destruction has received ample attention in the literature, detailed analyses of young entrepreneurs' financing, and especially the local conditions determining it, is still a novel field in economics and finance. Our estimates on this account demonstrate that local conditions are very important in determining the type and amount of financing entrepreneurs receive.. In this sense our paper is related to Black and Strahan (2002); Berkowitz and White (2004), Kerr and Nanda (2009; 2010).[8]

Our work also contributes to a larger literature that investigates the salient long-term determinants of economic growth and development (Engerman and Sokoloff (1997); Acemoglu, Johnson and Robinson (2001); Acemoglu, Johnson and Robinson (2002); Engerman and Sokoloff (2002); Nunn (2008)). Last but not least, the analysis also participates to a growing literature on finance and inequality. While most of the work in this area studies how finance may affect the degree of income or wealth inequality (see Demirgüç-Kunt and Levine (2009) for a review, and more recently Beck, Levine and Levkov (2010)), our paper studies how wealth inequality affects financial outcomes (and in this sense it is closer to Rajan and Ramcharan (2011) and Degryse, Lambert and Schwienbacher (2013)).

[8] See also Carlino and Kerr (2014), Kerr and Nanda (2014), and Quadrini and Rios-Rull (2014) for reviews.

The rest of the paper is organized as follows. Section II discusses the testable hypotheses and introduces in more detail our measures of wealth inequality. Section III discusses the results on local wealth inequality and firm ownership, financing and type and type. Section IV links local wealth inequality and bank presence and education, while Section V looks at judicial rulings. Section VI concludes.

II. Inequality and Corporate Outcomes

A. Testable Hypotheses

Our hypotheses are based on the work of Engerman and Sokoloff (1997), Engerman and Sokoloff (2002), and Perotti and von Thadden (2006). The first two papers describe how the emergence of wealthy elites may prevent the development of institutions designed to preserve their political power and to maintain the existing level of inequality. As a result, unequal societies will be characterized, amongst other things, by low level of education, less efficient capital markets and an ineffective judiciary system. Engermann and Sokoloff also describe the factors that can be underlying persistent differences in inequality: different climates and geographical environments that may favor one type of crop over another. Their argument suggests that climates that are best suited for large plantations, like sugar or tobacco, will induce relatively high economic inequality. The production of these crops comes at a high fixed cost; as a result, the market, in equilibrium, can support only a few farms. The outcome is thus a society controlled by few wealthy landowners. Conversely, climates supporting crops like wheat will result in more equal societies. The production of these crops do not require high fixed costs, hence the market can withstand more producers. These societies will be more equal and mainly composed by small landowners. A feature of this theoretical framework is

that inequality and "bad" institutions will be persistent over time and reinforce each other. Along these lines, Rajan (2009) also provides a theoretical framework and empirical evidence of how institutions may persist through time.

In Perotti and von Thadden (2006) the general thinking about how wealth inequality between individuals may eventually determine corporate financing (and also entrepreneurial dynamism) starts from the premise that individuals are generally risk-averse and will "choose" (i.e., "vote for" in a society that has a direct voting mechanism) those institutions that best represent their claims in companies. In addition to their human capital that is commonly distributed yet inherently non-diversifiable, wealthy individuals may also own diversifiable financial wealth. Now, wealth may be distributed unequally among individuals, i.e., many individuals including the so-called "median voter" then own mainly non-diversifiable human capital. If "banks" are more risk-averse than the "equity market", the median voter with mainly non-diversifiable human capital will opt for banks. If wealth is distributed more equally among individuals, on the other hand, the median voter is more likely to also own financial wealth in addition to her human capital and is more likely to vote for the equity market. The "family" as a saving mechanism is also typically considered to be more risk averse than the equity market.

Within this framework we can therefore derive five testable hypotheses concerning the effect of wealth inequality on corporate financing and entrepreneurial dynamism:

Hypothesis 1: As proprietorships are a simple corporate form often characterized by concentrated ownership and they usually are family owned, the likelihood that a start-up is a sole proprietorship as opposed to any other type of firm will be increasing in county inequality.

Hypothesis 2: Greater wealth inequality will lead firm owners to invest a larger fraction of own funds into the new business. Such an outcome may, amongst other things, reflect the existence of inefficient capital market or an entrepreneurial preference to pursue simple technologies that do not require much external finance. *Hence, greater wealth inequality will lead to, ceteris paribus, owner equity being a greater fraction of total financing.*

Hypothesis 3: Greater wealth inequality will lead, ceteris paribus, firm family and bank financing to be a larger fraction of total financing. To the extent that wealth inequality is associated with poor institutions and inefficient capital markets, entrepreneurs may rely to their own family to obtain the necessary resources. Similarly, bank debt contracts could be easier to enforce, in areas were law enforcement is weaker (see Modigliani and Perotti (2000)). In the spirit of Perotti and von Thadden (2006), as families or banks are typically considered to be a more risk averse source of financing compared to the 'outside' equity market, greater wealth inequality will lead to, ceteris paribus, firm family and bank financing to be a greater fraction of total financing.

Hypothesis 4: Greater wealth inequality will lead to, ceteris paribus, equity obtained from angels and venture capitalists to be a smaller fraction of total financing. This hypothesis is really a corollary of Hypothesis 3. Angels and venture capitalists are residual claimants on the profits a firm makes and therefore can be considered to induce risk taking more compared to banks, something that contradicts with the preferences of the median voter when she mainly owns non-diversifiable human capital. As a consequence equity markets will be less developed when inequality is greater, making the supply of angel and venture capital less prevalent in counties with larger inequality. To the extent that contracts are more difficult to

enforce or entrepreneurs prefer traditional technologies, equity finance should be less prevalent in unequal areas.

Hypothesis 5: In unequal societies entrepreneurs themselves may prefer simpler technologies or they may find difficult to finance riskier ventures. We therefore expect to see less high technology start-ups when county inequality is larger. *Hence, the probability that a new business venture will be a high tech firm will, ceteris paribus, decrease in county inequality.*

To summarize: The amount of 'inside' equity will be increasing in wealth inequality (*H1*, *H2*, *H3*), whereas the amount of 'outside' equity will be decreasing in it (*H4*). The amount of bank financing will be increasing in local inequality (*H3*). We expect the probability that a new business venture will be a high tech firm will, ceteris paribus, decrease in county inequality (*H5*).

B. Measuring Wealth Inequality

It is very difficult to obtain representative measures of wealth inequality at the county level, as result we construct two proxies for local wealth inequality. The first one is based on current levels of financial wealth and broadly based on the methodology introduced by Mian, Rao and Sufi (2013) intended to construct local level measures of household net worth; the second measure is based on historical records of land ownerships.

The contemporary measure of wealth inequality looks at the amounts of dividends and interests earned by US households in 2004, the first year in our sample period, as reported by Internal Revenue Service (IRS) Statistics of Income (SOI) data. The IRS-SOI data report the total amount of dividends and interest income received by US households in a certain zip code. The information is reported as a total per zip code, but also divided in five households'

income groups, ranging from low income to high income. Under the assumption that a typical household owns the market index for stocks and bonds, the amount of financial rents it receives depends only by the quantity of stocks and bonds it holds.

IRS-SOI provides three pieces of information important to construct our proxy.

a) The total number of households belonging to each income group;

b) For each income group, the number of households who declared non-zero dividend and non-zero interest income (for simplicity, we will call these non-zero households); and,

c) For each income group, the total amount of dividends and interests earned by all households.

We now report the procedure we adopted to construct our inequality proxy. For simplicity, we just describe the case where we consider only dividends as a financial rent. The procedure is exactly the same when we also include interest income. The procedure comprises six steps.

(1) We aggregate the IRS-SOI figures at a county level.

(2) For each county, we compute the number of households who declared zero dividend income and we place them into a separate category.

(3) For each county and each income group, we compute the average dividend earned by non-zero households. We do this by dividing the total amount of dividends for each income group by the respective number of non-zero households.

(4) We assume that each household in the same income group earned the average dividend computed in (2).

(5) We assume that each household owns the same type and composition of stock: the equity index. As a result, the amount of dividend received depends only on the quantity of stock owned.

(6) We use the number of non-zero households belonging to each income group, the number of households declaring zero dividends, and the average interests and dividend earned to compute a Gini coefficient that measures the distribution of dividend earnings within each county. Recall that the Gini coefficient is a measure of inequality that ranges between 0 and 1, where a coefficient close to 0 can be interpreted as full equality, whereas a coefficient of 1 indicates perfect inequality. We perform the same procedure with the interest income data.[9]

Table I provides an example of this computation. Column 1 lists the five income groups. Column 2 provides the number of households belonging to each income group. Column 3, the number of households declaring a non-zero dividend. Column 4, the sum of all dividends received by all households in each group. First, we compute the number of non-dividend earners by taking the difference between the total of Column 1 and Column 2, which we report in first row of Column 5. In remaining of Column 5, we copy and paste the number of households that declared dividends as in Column 3. We then compute the average dividend earned by non-zero households by dividing Column 4 by Column 3; we report these numbers in Column 6. We then compute the Gini coefficient, using six dividend income groups. The first one made of 1,576,927 households that earned zero dividends, the second made by 31,604 households that earn 1,181 dollars and up to the sixth group composed by 73,620 households that earned about 11,800 dollars in dividends. In this example, the Gini coefficient is equal to 0.91.

[Table I around here]

[9] As we do not know the amount of dividends and interest income each individual household declares we cannot compute a unique Gini coefficient based on the sum of these amounts.

Naturally, this is a proxy, and it may be subject to measurement error. It performs well in identifying perfect equality and perfect inequality. In the former case, we would observe each household earning the same financial rents independently of the income group it belongs to, and our Gini coefficient would correctly have the value of zero. In the latter situation, our data would reveal all households but one receiving a financial rent and the Gini coefficient would correctly receive the score of one. The proxy does not work very well in every situation where in each income group, the distribution of dividends is very dispersed around the mean. In all these situations, we underestimate the degree of inequality. Measurement error may produce biased estimates of the coefficients when relating wealth inequality to financial outcomes. We will be able to alleviate this problem by instrumenting this wealth inequality measure in various specifications.[10] We will present our main results using a Gini coefficient based on dividends. Results are basically the same if we use a Gini coefficient based on interest income.

To construct our historical measure of wealth inequality we obtain information on historical farm land sizes at the county level from the 1890 US Census. More precisely, for each county we have information on the total number of farms that – based upon their total acres of farm land – fall in a certain size bin. Farms are assigned to one of the following seven bins: Under 10 acres, from 10 to 19 acres, 20 to 49 acres, 50 to 99 acres, 100 to 499 acres, 500 to 999 acres, and 1,000 or more acres.

[10] Another possible source of measurement error may come from tax evasion. US financial institutions automatically report to the IRS dividends and interest income earned by their clients, making tax evasion through US banks virtually impossible, but taxpayers can avoid taxes by holding wealth through foreign banks.

First, we assume that the lower bound farm size of each bin is the average farm size of all the farms in this bin (for the first bin we set the lower bound equal to 0.001). Next, we use these lower bounds to calculate a county Gini coefficient in a similar way as in Rajan and Ramcharan (2011) for example, by using the formula introduced by Atkinson (1970):

$$Gini = 1 + \frac{1}{n} - [\frac{2}{m*n^2}] \sum_{i=1}^{n} (n - i + 1) y_i,$$

where m is the mean farm size, n the total number of farms and y_i each farm ranked in ascending order, in line with Rajan and Ramcharan (2011).

Notice that we are unable to calculate a Gini coefficient for those counties that became incorporated after 1890, as the information on 1890 farm size distribution is unavailable. For these counties we manually look up the 1890 counties which these missing counties were part of before incorporation and take (simple) averages of the corresponding Gini coefficients. As the entire State of Oklahoma was incorporated well after 1890 (in 1907) we only have information on those few counties (8) that existed when it was still a territory. Based upon the information from these counties we construct a State Gini coefficient which we use for all counties in Oklahoma. To calculate this State Gini coefficient we sum the number of farms in each bin across counties.[11]

In our dataset the average Land Gini coefficient is 0.44 and its standard deviation is 0.14. This is slightly lower compared to more contemporary measures of household wealth inequality at the aggregated level (contemporary measures of household wealth inequality at

[11] Results are unaffected if we exclude Oklahoma from the analysis.

the county level do not exist). For example, De Nardi (2004) shows that the Gini coefficient for the entire US is 0.78 based upon household wealth data from the Survey of Consumer Finances from 1989. Relying on the same survey, Wolff (2010) finds that the Gini coefficient is 0.83 in 2007.

We also find that 1890 land inequality display a 36 and 46 percent positive correlation with our measures of dividend and interest inequality. The historical measure is also correlated with other socio economic measures that may reflect the degree of wealth inequality. It displays a positive correlation with local poverty rates (43 percent) and the number of crimes per capita (33 percent) and it is negatively correlated with the number of white people (a rough proxy of the size of the middle class) living in a county (-53 percent).

III. Firm Ownership, Financing and Type

A. Data Sources with Information on Firm Ownership, Financing and Type

From the Kauffman Firm Survey (KFS) panel dataset we obtain the financial information for a five-year period from 2004 to (and including) 2008 on 4,928 individual US start-ups during their early years of operation (see Robb and Robinson (2014) for a comprehensive discussion of the capital structure choices of firms covered by the survey). This information is particularly useful to reconstruct the sources of financing of these young firms and allows us to distinguish between owner's own equity and external financing as well as between family, bank and venture capital financing.

Data on our main dependent variables is actually obtained from a restricted-access-only database, which is the so-called "Fourth Follow-Up Database" and which is a longitudinal survey. We analyze the 3,419 firms of the baseline survey that either survived over the entire

2005-2008 period or were specifically identified as going out of business during the same period. Hence, firms that dropped out in a specific year because their owners cannot be located or refuse to respond to the follow-up survey are not included in our analysis.[12] The dataset contains response-adjusted weights (which we use) to minimize the potential non-response bias in the estimates. From this database, we construct several crucial financial outcome variables, as well as control variables.

B. Dependent Variables

We study the impact of county equality on, in total, seven corporate outcome variables. Table II collects all definitions of all these dependent variables, and also of all controls, and indicates the relevant data sources. Table III provides summary statistics.

[Tables II and III around here]

For the purpose of summarizing we categorize the dependent variables into firm ownership, firm financing and firm type, though we recognize this categorization is not entirely descriptive. In terms of firm ownership, we feature the following twovariables (the estimates for these specifications will be reported in Table IV): *Firm Is Proprietorship* equals one if the firm is a proprietorship, and equals zero otherwise;[13] *Firm Equity* is the amount of equity invested (by up to a maximum of 14 owners) divided by total firm financing. From the

[12] This is common in the literature see Robb and Robinson (2014) and Berger, Cerqueiro and Penas (2014).

[13] We assign the value of one to the variable *Firm is Proprietorship* if a firm is either a sole proprietorship or a limited partnership. We assign all other firms the value of zero, i.e., these are firms that are classified as a limited liability firm, subchapter S-Corporations, C-Corporations, general partnerships or any other legal form. Alternatively defining a general partnership as a form of proprietorship does not change the results.

3,419 firms in our dataset 1,294 firms (38 percent) are proprietorships at the start of the sample period. Most firms (61+ percent) have at least one owner that invests her own equity into the firm during the first year of start-up. A quarter of all firms in our sample are even entirely financed by equity invested by the main owners in the first year of operations.

As firm financing variables we feature (the estimates will be in Table V): *Firm Angel and Venture Capital Financing* is the amount of equity obtained from angels and venture capitalists divided by total firm financing; *Firm Family and Bank Financing* is the total amount of business and owners' personal bank financing plus family financing divided by total firm financing.[14] [15] Finally, as the sole firm type variable we have: *Firm is High Tech* which equals one if the firm operates in a high technology industry, and equals zero otherwise.

Firms in our sample tend to rely little on equity obtained from angels and venture capitalists; only 4 percent of the firms make use of this type of financing at start-up. On average only 2 percent of total funding is obtained through these sources. The mean amount of equity from angels and venture capitalists at inception equals around $37,500. Contrary to equity obtained from angels and venture capitalists, start-ups tend to rely more on debt

[14] Family Financing is the amount of equity invested by parents and/or spouse. In the main analysis, we consider bank and family financing in the same dependent variable. In additional tests, we consider the two sources of financing as separate entities.

[15] It is evident from the descriptive statistics that a small percentage of firms rely on venture capital financing as well as bank financing. This generates many "zeros" in some of our dependent variable. To verify the robustness of our results in respect to this issue, we run two additional tests. First, we restrict our sample only to companies that rely on some form of external finance; this almost mechanically reduces the number of zeros by dropping from the sample firms that only rely on internal equity. Second, we keep the whole sample, but we transform the variables "bank and family financing" and "angels and venture capital financing" in (0/1) binary variables. We then run a rare event logit model (as in King and Zeng (2001)) and see if the explanatory power of our inequality measures still holds. In both robustness checks, inequality maintains the statistically and economic significance we observe in our main results.

financing in the form of bank and family financing (on average 11 percent of total financing comes from both business and owner's personal bank and family loans).[16]

We classify firms as being high technology intensive (*High Tech*) based upon the High Technology Industries NAICS list from the Science and Engineering Indicators 2006 from the NSF. Based upon this classification 31 percent of the firms are considered as being high tech at inception.

C. Control Variables

We have three sets of control variables, i.e., firm characteristics, main owner characteristics, and state and county characteristics. We discuss each of these sets of control variables now in turn.

1. Firm Characteristics

Total Assets is the logarithm of one plus total assets, which is the sum of cash, accounts receivable, product inventory, equipment or machinery, land and buildings, vehicles, other business owned property and other assets; *ROA* is the Return on Assets, i.e., the amount of net profit divided by total assets, which we winsorize at the 1 percent level; *Tangibility* is the amount of property, plant and equipment divided by total assets; and, *Number of Owners* is the logarithm of one plus the total number of owners.

In their first year of operations the start-ups in our dataset have total assets worth of, on average, $172,709. Some firms have a negative return on assets. For example, in the first year of operations 54 percent of all start-ups have a *ROA* below zero percent. Tangible assets make

[16] The largest part, 7 percent, comes from personal loans obtained by the owner(s). The average amount of bank financing that firms rely upon in our sample is $28,277 at inception.

up around 56 percent of total assets on average. However, 26 percent of the businesses report no tangible assets at all in the first year of business. The majority of firms (61 percent) have one owner, whereas the remaining 39 percent of businesses is owned by multiple owners.

2. Main Owner Characteristics

The main owner characteristics comprise five dummies that equal one if the condition embedded in its label is fulfilled, and equals zero otherwise. These main owner dummies are: *Is Female*, *Is African-American*, *Is Hispanic*, *Is Asian* and *Is Born in the US*. *Work Experience* is the number of years of work experience of the main owner in the firm's industry.

We identify the main owner in the same way as Robb and Robinson (2014), who consider the owner with the largest amount of equity invested to be the primary owner.[17] Overall, entrepreneurs of the nascent businesses in our sample are mostly white (only 15 percent is either African-American, Hispanic or Asian), male and born in the US. This is consistent with the owner characteristics of firm owners from the Survey of Consumer Finances (SCF) (see Puri and Robinson (2007)). Less than a third (27 percent) of the main owners is female, and only 9 percent is born somewhere outside of the United States. In addition, primary owners tend to have quite some work experience in the same industry as their new business is operating in, the average years of experience is a little less than 14 years (median of 11 years).

3. State and County Characteristics

As State characteristics we include its *GDP* which is the logarithm of one plus the gross domestic product of the State during the year.

[17] See their paper for the exact methodology on how to define the primary owner in case multiple owners invest an equal amount of equity into the firm.

As county characteristics we have: *Population* which is the total county population at year-end; the *Catholic to Protestant Ratio* which is the ratio of the total number of Catholics divided by the total number of Evangelicals in the county at year-end 2000; the *Personal Income Per Capita* which is the logarithm of one plus the per capita county personal income at year-end; the *Nonfarm Establishments Per Capita* which is the total number of nonfarm establishments divided by the total population in the county at year-end; *Wage Inequality* which is the Gini coefficient of wages earned in each US-county coming from the IRS-SOI data; the *Federal Government Expenditures Per Capita* which is the total Federal government expenditures in thousands of US Dollars during the year in the county divided by the total population in the county; and the *Land Area* which is the logarithm of one plus the total county area in square miles at year-end 2000.[18]

We include *GDP* to control for the state of the local economy and in the same line for per capita county personal income; their means respectively 10.65 and 10.48. With respect to county demographics, between counties there is considerable heterogeneity when it comes to religion, although on average Catholics outweigh Protestants by a factor of four. County federal government expenditures per capita differ quite a lot between counties as well; the 10^{th} percentile (of its logarithm) is 4 whereas the 90^{th} percentile is almost three times higher. Additionally, counties' Wage Inequality, as measured by the Gini coefficient based on incomes, is quite high, with a mean value of 0.55, but differs less substantially between counties: Its standard deviation is 0.04.

D. Results

[18] As we control both for population and land, we implicitly control for population density. Controlling directly for population density does not change our results.

1. Firm Ownership

We start by testing how local wealth inequality affects different measures of firm ownership. Table IV provides the first estimation results. We relate local inequality to the probability that a start-up is a sole proprietorship. We measure local inequality in two ways: Firstly, we create a contemporary Gini coefficient using information on households' wealth in the form of dividends obtained from the IRS tax filings from 2004. Secondly, we introduce an inequality measure that is based upon historical farm land data from 1890. To be able to make causal statements we account for possible endogeneity in several ways: Given that our second inequality measure is based upon historical farm land data from 1890 reverse causality is not likely to be an issue. In addition, to account for omitted variables because of unobserved heterogeneity at the state, year, industry, state-year and industry-year level that could affect our estimates, we introduce correspondingly a broad sets of fixed effects. Moreover, we instrument our contemporary inequality measure using information on average rainfall and temperatures in the spirit of Easterly (2007) and Rajan and Ramcharan (2011).

[Table IV around here]

We report the results in Table IV, using our contemporary measure of inequality based on households' financial wealth in Panel A and our historical county inequality measure based on the county land distribution from 1890 in Panel B respectively.

In Column 1 of Panel A in Table IV we start with our baseline estimation using a standard Linear Probability model.[19] We include firm, owner characteristics as well as state, year and industry fixed effects. In Column 2 we repeat the estimation but additionally include an extra set of county characteristics. Alternatively we include in specifications 3 and 4, next to the county characteristics also industry and state-year fixed effects and state-year and industry-year fixed effects, respectively. We see that local inequality matters. In all specifications we find, in line with Hypothesis 1 (H1), that the probability for a start-up to be a sole proprietorship increases in inequality. The point estimates increase slightly across columns. The effect we find is also economically significant and stable across specifications: A one standard deviation increase in county wealth inequality increases the probability for a start-up to be a sole proprietorship by around 14 percent (evaluated at the mean of the Proprietorship indicator variable).

These results are confirmed in Panel B, where we introduce a county measure of inequality based upon land distributions from 1890. Similar to Panel A we include in Column 1 in Panel B firm, owner characteristics as well as state, year and industry fixed effects. In Column 2 we add an additional set of county characteristics, whereas in Columns 3 and 4 we include industry and state-year fixed effects and state-year and industry-year fixed effects, respectively. The economic relevancy is somewhat lower than in Panel A: A one standard deviation increase in county wealth inequality increases the probability for a start-up to be a

[19] We prefer a linear probability model because the large number of fixed effects we eventually want to introduce may bias the maximum likelihood estimates due to the incidental parameter problem (for a review see e.g. Lancaster (2000)). In robustness we also run specifications using logit and probit models but the point estimates of our main independent variables as well as their statistical significance actually do remain mostly unaltered.

sole proprietorship by around 8 percent (again evaluated at the mean of the Proprietorship indicator variable).

Next we turn to H2. We explore how wealth inequality explains the proportion of firm equity that is held by its owners using Tobit model estimation.[20] Columns 5 to 8 present the results from our analyses. The results in Panel A include the contemporary measure of inequality and Panel B shows the results using an inequality measure based upon land distribution from 1890. Again, we include firm, owner and county characteristics as well as state, year and industry fixed effects in our baseline estimation in Column 5 and introduce an extra set of county controls in Column 6. We alternatively include industry and state-year fixed effects and state-year and industry-year fixed effects respectively in Columns 7 and 8.

Exploring the results in Panel A, where we use the inequality measure that is based upon contemporary financial wealth distributions, the results are not statistically significant throughout the specifications. Turning to Panel B, where we introduce our inequality measure based upon land distributions from 1890, the results illustrate that the fraction of equity owners hold in their firm increases in county inequality, suggesting that owners are either are forced to rely on 'inside equity' more compared to other sources of outside equity financing because of less efficient capital markets or simply do not require much external finance, when inequality is higher. The effect is substantial: The semi-elasticity for a one standard deviation change of inequality on firm equity ranges between 11 and 13 percent respectively.

[20] Maximum likelihood estimators of marginal effects in Tobit models are found to be overall much less biased due to the incidental parameter problem (than those in binary dependent variable models); but when many fixed effects are introduced, and expected biases in the slope estimators (in terms of marginal effects) do emerge, it is away from zero; at the same time the estimated standard errors may be biased towards zero (Greene (2004)). We therefore also re-estimate all specifications using linear models, but results are very similar.

2. Firm Financing

So far the results overall demonstrate that local wealth inequality matters for firm ownership. In this section and based on the models in recent papers by Modigliani and Perotti (2000) and Perotti and von Thadden (2006), we ask whether it also matters for the way in which start-ups are financed. To the extent that more unequal counties are characterized by less efficient capital markets, poorer institutions and law enforcement entrepreneurs may rely more on internal financing from family and friends as well as bank financing, given that bank debt contracts are relatively easy to enforce, but less on outside equity obtained from angel investors and venture capitalists. Table V presents the results of our Tobit analyses. Again we introduce our contemporary wealth inequality measure in Panel A and our county inequality measure based upon land distribution from 1890 in Panel B. We focus on the proportion of bank and family financing in Columns 1 to 4, controlling for the usual firm, owner and county controls as well as dense sets of fixed effects to capture unobserved state, year, industry, state-year and industry-year heterogeneity, respectively.

[Table V around here]

The results in Column 1 show that, in line with H3, the coefficient on county inequality is positive and statistically significant. The result indicates that a one standard deviation increase in county inequality increases the proportion of bank and family financing with 62 percent (of its own mean) when using a contemporary inequality measure, versus 33 percent when including our historical inequality measure. When including a set of county controls in Column 2 the semi-elasticity increases somewhat to 73 percent and the coefficients are all

statistically significant at conventional levels. When we add state-year and industry-year effects in Columns 3 and 4 the estimated coefficient on inequality is again statistically significant (at the 1 percent level) and implies that a one standard deviation increase in county inequality increases the proportion of bank and family financing with more than a half, around 70 percent when using our contemporary inequality measure and around 50 percent in Panel B when including an historical county inequality Gini coefficient.

Overall these findings are in line with both supply and demand of finance hypotheses. In more unequal societies, bank debt may be easier to enforce in court and, as a result, more commonly supplied. At the same time, in more unequal societies entrepreneurs may prefer to undertake simpler technologies requiring simpler forms of external financing for their businesses. In the remaining columns of Table V we explore, using Tobit estimation, how county inequality affects the proportion of angel and venture capital financing. For both measures of inequality the proportion of angel and venture capital financing decreases in county inequality, as we can see from the results in Columns 5 to 8. The coefficient on inequality is negative and statistically significant and robust across specifications, however the economic significance is larger in the specifications from Panel A, where we include our contemporary measure of inequality: A one standard deviation increase in county inequality decreases the proportion of angel and venture capital financing by a factor between 7 and 10 in Panel A,[21] and between 9 and 182 percent in Panel B. External equity financing is

[21] While these estimated effects appear large, notice that the mean percent angel and venture capital financing is quite small to begin with. Also recall that when expected biases in the slope estimators in Tobit due to the incidental parameter problem do emerge, it is away from zero, and that at the same time the estimated standard errors may be biased towards zero (Greene (2004)). Standard OLS analysis yields similar results with coefficients on the various measures of wealth inequality still negative and statistically significant.

decreasing in county inequality, either because of a lower supply, in line with what described in Perotti and von Thadden (2006), or a lower demand because entrepreneurs because entrepreneurs prefer more traditional technologies. The results in Table V show that local inequality matters for firm financing. The findings confirm (i.e., cannot reject) both H3 and H4 and are therefore consistent with the papers by Perotti and von Thadden (2006) as well as Modigliani and Perotti (2000).

Chen, Gompers, Kovner and Lerner (2010) show that the distribution of venture capitalists in the US is concentrated in three areas: San Francisco, Boston and New York.[22] We therefore verify whether our results are not simply driven by firms located in these areas by excluding all firms located in the States of California, Massachusetts and New York. We find that results are unaffected (and therefore not tabulated).

3. Firm Type

In the previous tables we find evidence in support of a greater prevalence of family and bank financing and less outside equity financing from angels and venture capitalists for firms in more unequal counties. But does the prevalence of bank financing have other spill-over effects? We present results on this possibility in Table VI, where we examine the effect of wealth inequality on firm type (H5). We construct a dummy variable that indicates whether a Firm is High Tech or not and run a Linear Probability model. As the definition of High Tech is based on the NAICS industry classification, we do not include industry fixed effects and trends in these regressions. Once again, we include firm, owner and county controls and broad

[22] Chen, Gompers, Kovner and Lerner (2010) reports that more than 49 percent of US based companies financed by venture capital firms are located in one of these three areas. The Kauffmann survey data we use combines venture capital with angel financing. The number of firms with non-zero angel and venture capital financing located in California, Massachusetts and New York corresponds to only 19 percent of the total number of firms, suggesting angel financing may be less concentrated.

sets of fixed effects in the different specifications. We also introduce both our inequality measures: Our contemporary county inequality measure in Panel A and the historical inequality measure in Panel B.

[Table VI around here]

Interestingly, the coefficient on county inequality is always negative and statistically significant at the 5 percent level, indicating that the likelihood that newly created firms are high-tech decreases in local inequality. The effects are also economically relevant. Depending upon specification, a one standard deviation increase in inequality decreases the likelihood that a Firm is High Tech between 4 to 8 percent of its mean when introducing a contemporary inequality measure in Panel A or between 5 and 7 percent in Panel B (when including an historical inequality measure). The results are suggestive of a possible side effect of a greater prevalence of bank financing in more unequal counties: A possible explanation for the negative effect of local inequality on the probability that a Firm is High Tech may be that banks are more willing to extend financing to conservative industries, making it difficult for new start-ups in more unconventional industries (such as high tech industries) to obtain bank financing in order to start up their business. Another explanation may be demand driven: In more unequal counties entrepreneurs may prefer simpler technologies themselves. We will explore possible supply and demand mechanisms in more detail in Section 5.

It also important to notice including controls in our regressions, leaves the relationship between wealth inequality and entrepreneurial outcomes unaltered or, in many cases, makes it ultimately stronger rather than weaker. To the extent that firms and state/county unobservable

characteristics are correlated to our controls, it appears that endogeneity works against finding any link between wealth inequality, start-up capital structure and technology choices (Altonji, Elder and Taber (2005); Bellows and Miguel (2006); Bellows and Miguel (2009)).

4. Instrumental Variable Analysis

Even though we take several measures to prevent our estimates to be biased because of unobserved variables that are correlated with both our independent variable of interest, i.e., county wealth inequality, and the dependent variables of interest,[23] we now rule out further any possible bias in our estimates by instrumenting our contemporary 2004 county inequality measure as well.

We use instruments for county wealth inequality in the spirit of Easterly (2007). The instrumental variables are based upon past local weather conditions, i.e., there are based on the historical rainfall and temperature between 1895 and 2003 and their corresponding standard deviations. More precisely, we obtain information from the National Climatic Data Center (NCDC) on local monthly precipitation and temperature (measured in inches and degrees Fahrenheit, respectively) and their corresponding standard deviations for the entire period between 1895 and 2003. We then construct simple averages of these series. The NCDC provides this weather information at the so-called "divisional" level, i.e., each state is subdivided in at most 10 divisions that are comprised of areas that are known to have similar climatic conditions. We assign each county to the state division it belongs to.

Our instrumental variable strategy is also inspired by Engerman and Sokoloff (2002) who already documented that the degree of inequality is partly determined by the local soil quality.

[23] Recall that we use an historical measure of county inequality to resolve reverse causality and that we saturate specifications with state, industry, state-year and/or industry-year fixed effects.

Their findings make the historical local weather conditions suitable instruments for inequality (of course to the extent that inequality is persistent through time) becomes local weather patterns likely fixed crop yields for cotton and tobacco which in turn determined the well-being of a small group of wealthy owners (in the US South). As already shown by Vollrath (2006) and Rajan and Ramcharan (2011), even within States there is a significant amount of diversity in term of temperature and rainfall. In Kansas and Texas for instance some counties experience a yearly rainfall average of 20 inches while others go beyond 40 inches. A bit less extreme but still important are the differences in Illinois, where some counties have an average rainfall of 28 inches while others have 30% more (about 36 inches). Similarly, in California some counties had an average temperature of 50 F while others have 64 F.

[Table VII around here]

The *'First Stage'* column in Table VII provides the results of the first stage regression from 2SLS regressions and indicates that indeed rain and temperature are significant determinants of current county inequality. All climate variable coefficients are statistically significant at the 1 percent level and enter with the expected sign: Higher rainfall levels and temperatures are associated with higher current county inequality, but at a decreasing rate as indicated by the negative signs on the coefficients of their respective standard deviations. In all the specifications the F-statistic of the first stage is well above 20, confirming that we have powerful first stages.

The following columns in Table VII report the second stage regressions for the dependent variables from Hypotheses 1 to 5, respectively. The results confirm our previous findings: In

more unequal counties start-up firms rely more on their own equity as well as bank and family financing. Moreover, they are more likely to be of a simpler business form, i.e., a proprietorship, and, although the coefficients are not statistically significant at conventional levels, also rely less on angel and venture capital financing and are less likely to be of a more complex high-tech nature. Again, the results are not only statistically significant but also very economically relevant: A one standard deviation increase in county inequality increases the reliance on an entrepreneurs' own equity with 36 percent (of its own mean), the probability that the start-up firm is of a simpler form (proprietorship) increases by half (52 percent increase of its mean) and increases the reliance on family and bank financing by 72 percent (again evaluated at its mean). Contrary to the OLS regressions, the IV regressions show a positive and statistically significant relationship between wealth inequality and owners' inside equity also for the contemporary measure of wealth inequality. The economic significance is important, a standard deviation increase of wealth inequality yields a 36% increase of the proportion of owner's equity to total finance.

IV. Opening the Black Box: Demand versus Supply Effects

Our analysis so far has identified a reduced form relationship between wealth inequality, capital structure and firms' technology choices. In the financial markets, such a relationship could be mediated both by supply and demand factors. For instance, wealth inequality may result into inefficient financial markets and restrictions to the supply of external finance. At the same time, inequality could be associated with a lower demand for external finance because of the entrepreneurs' education level. Less educated entrepreneurs may prefer to work

with simpler technologies and more traditional productions that require a lower amount of external finance, and in particular equity finance.

We use data both from Kauffmann survey and from the US Census to evaluate the relative importance of supply and demand factors in explaining our results. We will focus in particular on access to credit markets, as a supply factor, and on education, as a demand factor. In particular we will study whether entrepreneurs located in counties displaying high values of wealth inequality are less likely to have a college degree (or more). We will also use Census data and see whether in the aggregate by counties, education levels depend on the local inequality level.

As a measure of access to credit we follow Rajan and Ramcharan (2011) and use the number of bank establishments per capita. Rajan and Ramcharan (2011) show that in the 1930s US counties displaying more wealth inequality had a lower number of bank establishments per capita. They provide evidence that suggests such a result is more likely to indicate a lack of supply of financial capital rather than a lack of demand.

But first in Panel A of Table VIII we examine the effect of contemporary county inequality on the supply in bank financing, measured by the number of banks per 1,000 in capita (as in Rajan and Ramcharan (2011)). In Column 1 we include state and year fixed effects, whereas in Column 2 we add a comprehensive set of county characteristics. Column 3 presents the results from the second stage from a 2SLS IV regression where we instrument county inequality with the average historical rainfall, temperature and their standard deviations. The results indicate that inequality indeed hampers the supply of external financing: The county inequality coefficient is negative and statistically significant throughout specifications.

The results are also economically meaningful: A one standard deviation increase in inequality decreases the number of banks per 1,000 capita for example by around 9 percent of its mean in Columns 1 and 2 respectively. When we use our historical measure of county inequality in Panel B these results are confirmed: A one standard deviation increase in inequality decreases the number of banks per 1,000 capita for example by 10 and 5 percent of its mean in Columns 1 and 2 respectively. Again the coefficients are statistically significant at conventional levels as well.

[Table VIII around here]

Turning to education as a demand driven explanation for our reduced form findings pertaining to the firms' financing, we present the results in Columns 4 to 9 in Panel A, where we use the county inequality measure based upon households' financial wealth from 2004. In Columns 4 to 6 the results indeed support a demand driven explanation of education: In more unequal counties the percentage of adults with a college degree or higher is lower. In fact, a one standard deviation increase in county inequality decreases the percentage of adults with a college degree or more between 16 to 45 percent of its mean, depending upon specification. Moreover, the population inflow of educated individuals (i.e., those with at least a college degree) is also lower in more unequal counties, as can be seen in Columns 7 to 9. A one standard deviation increase in inequality results in a lower inflow. The economic effect is also sizable however: A decrease between 30% and 50% percent evaluated at the mean of county inflow. However, in Panel B, when using the historical inequality measure, the result on the percentage of adults with at least a college degree is not statistically significant in Column 4.

The result on the population inflow of educated individuals is also not statistically significant in Column 6.

Overall, it can be concluded that the results suggest evidence in favor of both supply and demand factors in explaining the reduced form findings of the relationship between county inequality and firms' financing.

V. Disentangling Models: The Election of Judges

In the previous section we found evidence consistent with the notion that the relationship between wealth inequality and finance is mediated both by demand and supply factors.

While the general framework put forward by Engerman and Sokoloff (1997) and Engerman and Sokoloff (2002) encompasses both supply and demand channels, Perotti and von Thadden (2006) is concerned in particular with the supply side of finance: Citizens decide who are going to be the main suppliers of finance in their constituencies. In this section, we see whether voting and the general preferences of the public may have a role in shaping the local financial system. In the spirit of Perotti and von Thadden (2006), voting is the mechanism that allows citizens to express their own preferences. However, thinking about the relationship between the quality of institutions and inequality, election outcomes and resultant policymaking will also be influenced by campaign contributions and lobbying by or on behalf of the wealthy elite, an idea consistent with Engermann and Sokoloff`s work.

We take to the data the key ingredients of these frameworks, that is, agents can vote. We will provide some indirect evidence to see whether the local level of wealth inequality has an impact on voting outcomes and whether this impact is determined by pure citizens' preferences or by some campaign contribution or lobbying activity.

Our geographical unit of analysis is again the US County. We look at a county-level institution that (at least in many US States) citizens are called to elect, i.e., judges of first degree courts. In particular, we examine whether, in more unequal counties, the decisions of judges in civil cases are more likely to favour banks over businesses (or broadly speaking equity). We will also provide some suggestive evidence that will discern whether voting results are mainly driven by people's preferences or are more related with lobbying activities.

We obtain data on civil trials from Westlaw US, a database that contains opinions and descriptions of US trials since 1948. A limitation of the Westlaw database is that it only contains information about second degree trials.[24] Luckily, from the discussion of the second degree hearings we can obtain vital information about the first degree trial which we use in our analysis. We collect data for a 30 years period, i.e., between 1984 and 2014.

To select the data we employed the following procedure. We restricted our search to civil trials. We searched for civil trials that involved either a bank or a business as one of the parties. We made a keyword search for party names specifying the search to be restricted to the words "bank" and "partnership", "business" or "corporation". The output we obtained still contained many cases where a bank was facing an individual in a business unrelated case. We resolved this problem by manually selecting the cases in which a bank was actually facing a business.

The Westlaw trial report contains the name of the county where the first degree trial took place, the name of the parties involved, whether the first degree trial was a summary

[24] This will generate selection bias in our analysis as it is very likely that second degree cases are not a random sample of the whole population of trials in a county. It is very difficult to give an account of the importance and the direction of the bias. To the extent that second degree cases are the most controversial or somehow they deal with "new situations", the bias may actually be beneficial for our analysis. These are the situations where the discretion of the judge is more important in deciding the case, which is exactly what we want to capture.

judgment, and brief description of the case which includes the result of the first degree trial. Westlaw also reports the West Headnotes of each trial. West Headnotes are a standard categorization which divides the law into major categories (for example *deposit and escrows*, *contracts*, *compromise and settlement*). We use these basic categories to create case (categories) dummies.

Each West Headnotes major category is also divided in various subcategories. In principle, each trial may belong to various West Headnotes subcategories depending on its nature and its complexity. We counted the number of subcategories each trial belongs and consider this a proxy for the complexity of the case. In principle, cases that belong to more subcategories should be more complex.

From the Westlaw report we also use some information items related to the second degree trial. In particular, whether the second degree sentence involved dissenting judges or not: We consider this another proxy of the complexity of the case. We also check whether the first degree sentence was affirmed or not in second degree.

We read the description of the first degree trials and determined whether the bank won it or not. We define as a victory a situation where the bank obtained in full what requested to the court, if the bank was a plaintiff, or a situation where the request of the opposing party was denied, when the bank was a defendant.

The process of judicial selection and the length of their appointments differs considerably between States. A total of 20 States elect its own judges. Some States (in total 7) have implemented a Partisan election as the mode of selection, where the candidates are listed on the ballot along with a label designating the political party's ballot on which they are running; in other States judges are not affiliated with a political party on the ballot (for example the so-

called Non-partisan and Missouri Plan selection methods). In principle, in States that select their judges via elections it is possible for voters to select a judge that best coincides with their preferences.

Partisan elections and length of the term in office have been usually considered as measures of judicial independence (Hanssen (2004a)). Judges are more likely to be independent from their own constituency the longer they stay in office, as they do not need to face an imminent re-appointment. In partisan elections the importance of campaigning and campaign contributions tends to be an important factor to increase judges' chances of being selected.

In principle, our empirical analysis would provide some support to Perotti and von Thadden (2006) if we find that in counties that are more unequal, judges are more likely to rule in favor of banks. This effect should be stronger in counties where judges are elected. The institutional story would predict a stronger relationship between wealth inequality and judicial decisions in counties where judges are less independent, in other words were judges stay in office for a shorter period of time and face partisan elections.

To test this hypothesis we create a dummy called *Elected* which we code to be equal to 1 if a firm is located in a State/County where judges are elected. We also code a partisan dummy *Partisan* which to be equal to 1 if a firm is located in a State where judges are elected based upon a Partisan election and 0 otherwise. In both cases, we interact the dummy variable with our inequality measure. We also control for the length of the term in office of judges and also interact it with the inequality measure.[25] Since, our data starts in 1984, we consider here only

[25] In Rhode Island, Vermont and Massachusetts judges have life time appointments. We set their values equal to infinity and employ a monotonic transformation of all values of the term in office (*tio*): $\frac{1-e^{-tio}}{1+e^{-tio}}$.

the predetermined historical measure of inequality. Table XI presents the results of this analysis. Each regression controls for state fixed effects, years fixed effects and case fixed effects using the West Headnotes. We consider particularly important this last set of controls, as it absorb every specificity regarding any particular topic that may affect judges' decisions. The regressions also control for a dummy that takes the value of 1 if the Bank was a plaintiff in the case. As the plaintiff usually choses the trial court, the dummy controls whether banks systematically chose "friendly" courts.[26]

[Table XI about here]

Column 1 presents the effect of local wealth inequality on the probability that a judge will rule in favor of a bank. The coefficient on County Inequality 1890 is negative and not statistically significant. Column 2 of Table XI considers the interaction between Wealth inequality and whether the State elects its judges. Also in this case neither wealth inequality alone nor the interaction term is statistically significant. In Column 3, we interact wealth inequality with the partisan dummy: The coefficient of the interaction term is positive and statistically significant. In more unequal counties where judges are elected, banks are more likely to win first degree civil trials. The economic effect is also sizable: A standard deviation increase in wealth inequality leads to an increase of about 15 percent of the probability that the bank will win the case. Columns 4 and 5 consider the same interaction term, but also

[26] In many of the trials we obtain from Westlaw it is not possible to see who were the original plaintiffs in the case, because Westlaw only reports who are the appellants and appellees. By considering in our analysis only those cases where the plaintiff is clearly identified we lose almost 600 observations. However our results remain otherwise unaffected if we consider the larger sample for which we cannot control in the specifications whether the bank was a plaintiff or not.

consider whether those banks that are plaintiffs or banks headquartered in the States where the trial takes place are more likely to win in partisan States. These additional controls are never statistically significant and more importantly, the coefficient on the interaction between County Inequality and Partisan remains unaltered.

Columns 6 to 9 look at the interaction between County Inequality and Judges' Length of the term in office. The coefficient on County Inequality alone is now positive and statistically significant while the coefficient on the interaction term is negative and also statistically significant. On average, in unequal counties, judges are more likely to decide in favor of banks, but this effect fades away the longer is the term a judge officially may remain in office. Taken altogether, these results suggest that the degree of judicial independence matters in determining judges' decisions in counties that display larger levels of wealth inequality. Hence, they provide some support on institutional explanations for the relationships between inequality and financial decisions in the spirit of Engerman and Sokoloff (2002).[27]

VI. Conclusions

We empirically test hypotheses emanating from recent theory showing how household wealth inequality may determine corporate financing and entrepreneurial dynamism. Local wealth inequality may be associated with poorer institutions leading entrepreneurs to choose simpler corporate forms for their businesses and to rely on internal finance or on bank and family finance. Wealth inequality may also lead risk-averse individuals to vote for those

[27] We also run specifications that include state and case trends. The estimated coefficients on the interaction terms between wealth inequality and length of the judicial terms remained virtually unaffected (both in terms of statistical significance and in terms of economic relevance). The interaction terms between wealth inequality and the partisan elections dummy maintain their original signs, but lose statistical significance.

institutions that best represent their claims in companies (see Perotti and von Thadden (2006)).

To test the hypotheses emanating from these frameworks we employ two measures of wealth inequality: One based on the current distributions of dividends and another one that relies on the distribution of land holdings within US Counties in 1890. To overcome endogeneity problems, we saturate specifications with comprehensive sets of fixed effects and characteristics and we estimate instrumental variable models.

The estimated coefficients suggest that county-level wealth inequality robustly increases sole-ownership and the proportion of equity, family and bank financing, yet decreases angel and venture capital financing. Inequality further reduces the likelihood local firms are high-tech.

The effects of wealth inequality on entrepreneurs' financing and technology could be mediated by factors both related to supply as well as to demand. We find evidence consistent with both supply and demand channels playing a role. On the supply side, we find that in more unequal counties, there are fewer bank establishments per capita consistent with the existence of local credit rationing. On the demand side, we find that in more unequal counties entrepreneurs are less likely to have a college degree (or higher). In principle, these are the entrepreneurs that could be more likely to work with traditional technologies that require simpler forms of financing.

In the last part of our analysis, and motivated by theories that rely on median voter outcomes, we assess whether locally-elected judges of the first-degree courts favour banks over equity. In particular, we examine whether in more unequal counties the decisions of judges in civil cases are more likely to go in favour of banks than in favour of businesses (that

we take to represent equity). We find that when inequality is severe, judges are more likely to rule in favour of banks in States that elect judges via partisan elections or where judges stay in office for only a short term period. As partisan elections or the length of term in office are likely to be related to judicial independence as well, we find these results to be consistent with theories that suggest that banks may be part of or are captured by wealthy elites.

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TABLE I

EXAMPLE COUNTY INEQUALITY 2004 CONSTRUCTION

Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Total No. of Returns	Taxable Dividends: No. Of returns	Taxable Dividends: Total Amount Reported	No. of Returns	Average Dividend per household	Taxable Interest: No. Of Returns	Taxable Interest: Total Amount Reported
Income Group Category by Size of Adjusted Gross Income and Zip-Code							
Total	1,882,964	306,037	1,287,291	1,576,927	0.00	651,013	1,189,469
Under $10,000	387,555	31,604	37,351	31,604	1.18	67,710	70,567
$10,000 under $25,000	553,957	42,503	64,756	42,503	1.52	114,076	150,519
$25,000 under $50,000	454,236	60,982	104,993	60,982	1.72	152,215	184,266
$50,000 under $75,000	231,139	55,051	113,500	55,051	2.06	123,892	156,056
$75,000 under 100,000	124,646	42,277	98,721	42,277	2.34	84,098	116,665
$100,000 or more	131,431	73,620	867,970	73,620	11.79	109,022	511,396

NOTES. The table provides an example of the data used to construct our *County Inequality* measure from 2004. We obtain data from the SOI (Statement of Income)database from the IRS on the total number of tax returns in thousands (one per household)filed in 2004 classified by zipcode and the adjusted gross income as shown in Column (1). In addition we obtain information on the number of returns that declared to have obtained a dividend and the accompanying total dividend amounts reported (reported in thousands and thousands of US $), again classified by zipcode and the adjusted gross income of the household (shown in Columns (2) and (3) respectively). Based upon this data we calculate the average dividend amount per household reported for each income group in Column (5). The average dividend amount is reported in thousands of US $. We create an extra category of the number of households that did not declare any dividend (which is the total reports filed minus all reports that declared a dividend) which we report in the row 'Total', coulmn (4) and (5) respectively. We use these average dividends as well as the income group classification to construct a Gini index in line with Rajan (2011). We create a second Gini coefficient in the same way, only now based upon the amount of interests received by households in 2004, as reported in Columns (6) and (7). Again, we obtain this information from the SOI database. The correlations between the Gini's based upon dividends and interest income received by households is very large and we therefore only report the results from our anlysis in which we introduce the county inequality measure based upon dividends received.

TABLE II

VARIABLE NAMES, DEFINITIONS, AND DATA SOURCES FOR THE EMPIRICAL ANALYSIS OF FIRM OWNERSHIP, FINANCING AND TYPE

Variable Name	Variable Definition	*Source*
Dependent Variables		
Firm Is Proprietorship	= 1 if firm is a proprietorship, = 0 otherwise	*KFS*
Firm Equity	The amount of equity invested by up to 14 owners divided by total firm financing	*KFS*
Firm Angel and Venture Capital Financing	The amount of equity obtained from angels and venture capitalists divided by total firm financing	*KFS*
Firm Bank and Family Financing	The amount of business and owners' personal bank financing and the amount of equity invested by parents and/or spouse divided by total firm financing	*KFS*
Firm is High Tech	= 1 if firm operates in a high technology industry, = 0 otherwise	*NSF*
Main Independent Variables		
County Inequality in 2004	The Gini coefficient of the distribution of wealth as measured by the distribution of the amount of declared dividends from household tax filings in the county	*IRS*
County Inequality in 1890	The Gini coefficient of the distribution of farm land in 1890 in the county (for counties in Oklahoma the state-level coefficient is used)	*USC*
Instrumental Variables		
Rain	The average district precipitation between 1895-2003, where a district is defined as a group of clustered counties with similar climatic conditions	*NCDC*
Temperature	The average district temperature in degrees between 1895-2003, where a district is defined as a group of clustered counties with similar climatic conditions	*NCDC*
Control Variables		
Firm Characteristics		
Firm Total Assets$_{t-1}$	The logarithm of one plus total assets, which is the sum of cash, accounts receivable, product inventory, equipment or machinery, land and buildings, vehicles, other business owned property and other assets	*KFS*
Firm ROA$_{t-1}$	Return on Assets, i.e., the amount of net profit divided by total assets winsorized at the 1% level	*KFS*
Firm Tangibility$_{t-1}$	The amount of property, plant and equipment divided by total assets	*KFS*
Firm Number of Owners$_{t-1}$	The logarithm of one plus the total number of owners	*KFS*
Main Owner Characteristics		
Main Owner Is Female	= 1 if main owner is a female, = 0 otherwise	*KFS*
Main Owner Is African-American	= 1 if main owner is African-American, = 0 otherwise	*KFS*
Main Owner Is Hispanic	= 1 if main owner is Hispanic, = 0 otherwise	*KFS*
Main Owner Is Asian	= 1 if main owner is Asian, = 0 otherwise	*KFS*
Main Owner Is Born in the US	= 1 if main owner was born in the US, = 0 otherwise	*KFS*
Main Owner's Work Experience	Number of years of work experience of the main owner in the firm's industry	*KFS*
State and County Characteristics		
State GDP$_{t-1}$	The logarithm of one plus the gross domestic product of the state during the year	*USC*
County Population	Total county population at year-end	*USC*
County Catholic to Protestant Ratio	Ratio of the total number of Catholics divided by the total number of Evangelicals in the county at year-end 2000	*ARDA*
County Personal Income Per Capita	The logarithm of one plus the per capita county personal income at year-end	*BEA*
County Nonfarm Establishments Per Capita	Total number of nonfarm establishments divided by the total population in the county at year-end	*USC*
County Wage Inequality	The Gini coefficient of the distribution of wages as measured by the distribution of the amount of labor from household tax filings in the county	*IRS*
County Federal Government Expenditures Per Capita	Total Federal government expenditures in thousands of US Dollars during the year in the county divided by the total population in the county	*USC*
County Land Area	The logarithm of one plus the total county area in square miles at year-end 2000	*USC*

NOTES. The table defines the variables used in the empirical analysis of firm ownership, financing and type, as well as the corresponding data sources used. Total firm financing is the sum of total debt and equity financing. *t-1* indicates a one year lag is used in the empirical analysis. Data sources include: *ARDA* = Association of Religion Data Archives; *BEA* = Bureau of Economic Analysis; *IRS* = Internal Revenue Service; *KFS* = Kauffman Firm Survey; *NCDC* = National Climatic Data Center; *NSF* = National Science Foundation; *USC* = US Census.

TABLE III

DESCRIPTIVE STATISTICS FOR THE EMPIRICAL ANALYSIS OF FIRM OWNERSHIP, FINANCING AND TYPE

Variable Name	Number of Observations	Mean	Standard Deviation	10%	Median (50%)	90%
Dependent Variables						
Firm Is Proprietorship	14,051	0.35	0.48	0	0	1
Firm Equity	10,377	0.36	0.41	0.00	0.15	1.00
Firm Angel and Venture Capital Financing	7,229	0.02	0.11	0.00	0.00	0.00
Firm Bank and Family Financing	10,540	0.11	0.25	0.00	0.00	0.50
Firm is High Tech	15,328	0.31	0.46	0	0	1
Main Independent Variable						
County Inequality in 2004	13,875	0.85	0.05	0.79	0.85	0.90
County Inequality in 1890	13,908	0.44	0.14	0.28	0.42	0.64
Instrumental Variables						
Rain	12,757	3.04	1.08	1.35	3.16	4.35
Temperature	11,787	54.73	8.45	45.12	52.89	68.92
Control Variables						
Firm Characteristics						
Firm Total Assets	14,015	9.41	3.71	1.79	10.23	12.91
Firm ROA	12,016	0.26	2.26	-0.91	0.04	1.67
Firm Tangibility	12,602	0.56	0.37	0.00	0.64	1.00
Firm Number of Owners	14,039	0.91	0.40	0.69	0.69	1.39
Main Owner Characteristics						
Main Owner Is Female	14,006	0.27	0.44	0	0	1
Main Owner Is African-American	14,050	0.07	0.25	0	0	0
Main Owner Is Hispanic	14,050	0.04	0.20	0	0	0
Main Owner Is Asian	14,050	0.04	0.20	0	0	0
Main Owner Is Born in the US	13,997	0.91	0.29	1	1	1
Main Owner's Work Experience	14,002	13.49	10.96	1	11	30
State and County Characteristics						
State GDP	13,875	10.65	0.14	10.51	10.64	10.80
County Population	13,875	905,644	1,557,066	42,269	405,142	2,015,355
County Catholic to Protestant Ratio	13,870	4.14	6.29	0.18	1.84	11.52
County Personal Income Per Capita	13,875	10.48	0.54	10.17	10.47	10.85
County Nonfarm Establishments Per Capita	13,875	0.03	0.01	0.02	0.03	0.03
County Wage Inequality	13,875	0.55	0.04	0.50	0.54	0.60
County Federal Government Expenditures Per Capita	13,875	7.46	6.62	3.99	6.34	11.07
County Land Area	13,875	14.41	0.64	13.78	14.46	15.06

NOTES. The table provides the number of observations, mean, standard deviation, 10th percentile, the median (50th percentile) and the 90th percentile of all variables used in the empirical analysis. Due to confidentiality the minimum and maximum are not reported.

TABLE IV
MAIN SPECIFICATIONS EXPLAINING FIRM OWNERSHIP

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	*Firm is proprietorship*				*Firm Equity*			
Panel A: County Inequality in 2004								
County Inequality in 2004	0.939***	1.016***	1.028***	1.023***	-0.0450	-0.359	-0.387	-0.445
	(0.260)	(0.250)	(0.253)	(0.252)	(0.528)	(0.547)	(0.551)	(0.909)
Firm Total Assets$_{t-1}$	-0.0517***	-0.0522***	-0.0529***	-0.0530***	-0.0930***	-0.0932***	-0.0935***	-0.0935***
	(0.00508)	(0.00517)	(0.00526)	(0.00524)	(0.00831)	(0.00847)	(0.00840)	(0.0000861)
Firm ROA$_{t-1}$	0.0100***	0.00917***	0.00943***	0.00924***	-0.0386***	-0.0374***	-0.0377***	-0.0366***
	(0.00269)	(0.00274)	(0.00274)	(0.00270)	(0.00695)	(0.00677)	(0.00691)	(0.000404)
Firm Tangibility$_{t-1}$	0.197***	0.182***	0.183***	0.183***	0.292***	0.302***	0.309***	0.308***
	(0.0221)	(0.0225)	(0.0231)	(0.0230)	(0.0510)	(0.0519)	(0.0526)	(0.00174)
Firm Number of Owners$_{t-1}$	-0.368***	-0.367***	-0.367***	-0.368***	-0.0181	-0.0102	-0.00682	-0.00613***
	(0.0431)	(0.0427)	(0.0433)	(0.0444)	(0.0636)	(0.0616)	(0.0601)	(0.000789)
Main Owner Is Female	0.0554**	0.0564**	0.0561**	0.0551**	0.0846*	0.0826*	0.0902*	0.0892***
	(0.0243)	(0.0247)	(0.0250)	(0.0253)	(0.0488)	(0.0501)	(0.0497)	(0.00240)
Main Owner Is African-American	-0.0339	0.00147	-0.000537	-0.00403	0.330***	0.323***	0.298***	0.308***
	(0.0445)	(0.0444)	(0.0447)	(0.0452)	(0.0673)	(0.0702)	(0.0684)	(0.00369)
Main Owner Is Hispanic	-0.0273	-0.0102	-0.0111	-0.0124	-0.0226	-0.0206	-0.0236	-0.0235***
	(0.0798)	(0.0773)	(0.0784)	(0.0798)	(0.0672)	(0.0659)	(0.0695)	(0.00407)
Main Owner Is Asian	-0.0206	-0.00568	-0.00499	-0.00552	-0.0453	-0.0416	-0.0686	-0.0646***
	(0.0504)	(0.0478)	(0.0484)	(0.0493)	(0.0902)	(0.0881)	(0.0846)	(0.00488)
Main Owner Is Born in the US	0.0886**	0.0663*	0.0667*	0.0670*	-0.0725	-0.0768	-0.0812	-0.0784***
	(0.0361)	(0.0349)	(0.0352)	(0.0355)	(0.0693)	(0.0676)	(0.0681)	(0.00110)
Main Owner's Work Experience	0.000117	0.000208	0.000241	0.000235	0.00300*	0.00270	0.00304*	0.00299***
	(0.000749)	(0.000728)	(0.000735)	(0.000742)	(0.00176)	(0.00178)	(0.00175)	(0.0000836)
State GDP$_{t-1}$	0.0150	0.110	--	--	-1.069	-0.815	--	--
	(0.152)	(0.151)	--	--	(0.658)	(0.657)	--	--
Semi-Elasticity of the Interaction Term for a St. Dev. Change in County Inequality	13.32%	14.41%	14.58%	14.51%	-0.62%	-4.98%	-5.37%	-6.17%
Dependent variable	*Firm is proprietorship*				*Firm Equity*			
Panel B: County Inequality in 1890								
County Inequality in 1890	0.0906	0.230***	0.224***	0.222***	0.335**	0.305*	0.299*	0.327***
	(0.0808)	(0.0805)	(0.0814)	(0.0801)	(0.155)	(0.174)	(0.169)	(0.00176)
Firm Total Assets$_{t-1}$	-0.0516***	-0.0521***	-0.0527***	-0.0528***	-0.0917***	-0.0921***	-0.0924***	-0.0924***
	(0.00502)	(0.00507)	(0.00517)	(0.00515)	(0.00833)	(0.00841)	(0.00838)	(0.0000877)
Firm ROA$_{t-1}$	0.0103***	0.00940***	0.00964***	0.00948***	-0.0387***	-0.0379***	-0.0380***	-0.0368***
	(0.00282)	(0.00287)	(0.00288)	(0.00285)	(0.00689)	(0.00678)	(0.00693)	(0.000409)
Firm Tangibility$_{t-1}$	0.202***	0.186***	0.186***	0.187***	0.297***	0.305***	0.308***	0.307***
	(0.0216)	(0.0220)	(0.0226)	(0.0224)	(0.0508)	(0.0516)	(0.0524)	(0.00176)
Firm Number of Owners$_{t-1}$	-0.368***	-0.367***	-0.366***	-0.368***	-0.0176	-0.00969	-0.00572	-0.00561***
	(0.0440)	(0.0432)	(0.0438)	(0.0449)	(0.0631)	(0.0616)	(0.0600)	(0.000780)
Main Owner Is Female	0.0574**	0.0594**	0.0591**	0.0582**	0.0923*	0.0901*	0.0957*	0.0947***
	(0.0251)	(0.0255)	(0.0258)	(0.0261)	(0.0487)	(0.0505)	(0.0501)	(0.00240)
Main Owner Is African-American	-0.0210	0.0146	0.0128	0.00922	0.323***	0.320***	0.298***	0.308***
	(0.0436)	(0.0442)	(0.0443)	(0.0448)	(0.0649)	(0.0682)	(0.0668)	(0.00368)
Main Owner Is Hispanic	-0.0159	0.000252	-0.000677	-0.00206	-0.0299	-0.0292	-0.0326	-0.0343***
	(0.0839)	(0.0821)	(0.0834)	(0.0846)	(0.0652)	(0.0644)	(0.0677)	(0.00397)
Main Owner Is Asian	-0.0304	-0.0140	-0.0136	-0.0143	-0.0677	-0.0625	-0.0774	-0.0739***
	(0.0520)	(0.0487)	(0.0495)	(0.0505)	(0.0896)	(0.0876)	(0.0852)	(0.00506)
Main Owner Is Born in the US	0.0776**	0.0522	0.0526	0.0528	-0.0803	-0.0870	-0.0870	-0.0839***
	(0.0362)	(0.0344)	(0.0348)	(0.0350)	(0.0699)	(0.0695)	(0.0706)	(0.00113)
Main Owner's Work Experience	0.0000452	0.000197	0.000228	0.000221	0.00317*	0.00295*	0.00327*	0.00322***
	(0.000738)	(0.000697)	(0.000704)	(0.000711)	(0.00174)	(0.00177)	(0.00175)	(0.0000817)
State GDP$_{t-1}$	0.0459	0.160	--	--	-0.961	-0.691	--	--
	(0.160)	(0.154)	--	--	(0.648)	(0.651)	--	--
Semi-Elasticity of the Interaction Term for a St. Dev. Change in County Inequality	3.60%	9.13%	8.89%	8.82%	13.01%	11.85%	11.62%	12.70%
County Control Variables	No	Yes	Yes	Yes	No	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	--	--	Yes	Yes	--	--
Year Fixed Effects	Yes	Yes	--	--	Yes	Yes	--	--
2-digit Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Year Fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes
Industry*Year Fixed Effects	No	No	No	Yes	No	No	No	Yes
Number of Observations Panel A	8,576	8,529	8,536	8,536	6,251	6,214	6,218	6,218
Number of Observations Panel B	8,519	8,470	8,477	8,477	6,215	6,176	6,180	6,180

NOTES. Models (1) to (5) are estimated with a linear probability model, while Models (7) to (11) are estimated with a tobit model left censored at 0 and right censored at 1 in Panel A. All models take into account cross-sectional Kauffman Firm Survey weights. The definition of the variables can be found in Table I. *t-1* indicates a one year lag. "Yes" indicates that the set of fixed effects is included. "No" indicates that the set of fixed effects is not included. "--" indicates that the indicated set of characteristics or fixed effects are comprised in the wider included set of fixed effects. Standard errors are clustered at the state level. P-values are given in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

TABLE V

MAIN SPECIFICATIONS EXPLAINING FIRM FINANCING

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	*Firm Bank and Family Financing*				*Firm Angel and Venture Capital Financing*			
Panel A: County Inequality in 2004								
County Inequality in 2004	1.420**	1.660**	1.638**	1.722***	-2.868***	-3.606***	-3.901***	-3.568***
	(0.606)	(0.675)	(0.674)	(0.00106)	(0.00251)	(0.00179)	(1.048)	(0.00155)
Firm Total Assets$_{t-1}$	0.121***	0.121***	0.123***	0.123***	0.104***	0.113***	0.105***	0.102***
	(0.0119)	(0.0119)	(0.0116)	(0.0000803)	(0.000214)	(0.000196)	(0.0336)	(0.000169)
Firm ROA$_{t-1}$	-0.0204	-0.0221*	-0.0225	-0.0224***	-0.104***	-0.105***	-0.105***	-0.102***
	(0.0135)	(0.0134)	(0.0138)	(0.000522)	(0.00116)	(0.00126)	(0.0296)	(0.00157)
Firm Tangibility$_{t-1}$	0.196***	0.191***	0.198***	0.195***	0.0194***	0.0426***	0.0236	0.0237***
	(0.0511)	(0.0511)	(0.0505)	(0.00214)	(0.00528)	(0.00491)	(0.0911)	(0.00464)
Firm Number of Owners$_{t-1}$	-0.00410	-0.00299	-0.000246	0.00221***	0.462***	0.453***	0.471***	0.450***
	(0.0603)	(0.0617)	(0.0595)	(0.000843)	(0.00235)	(0.00237)	(0.0638)	(0.00240)
Main Owner Is Female	-0.0184	-0.0241	-0.0259	-0.0249***	-0.245***	-0.250***	-0.270***	-0.292***
	(0.0507)	(0.0508)	(0.0506)	(0.00261)	(0.00726)	(0.00754)	(0.0949)	(0.00966)
Main Owner Is African-American	-0.178**	-0.157*	-0.155*	-0.160***	0.0733***	0.0522***	0.104	0.190***
	(0.0910)	(0.0917)	(0.0918)	(0.00428)	(0.00928)	(0.00982)	(0.127)	(0.0144)
Main Owner Is Hispanic	0.0225	0.0238	0.0187	0.00946*	0.339***	0.326***	0.299***	0.347***
	(0.0706)	(0.0695)	(0.0689)	(0.00489)	(0.00989)	(0.0112)	(0.0820)	(0.0119)
Main Owner Is Asian	-0.0292	-0.0179	-0.0225	-0.0347***	0.194***	0.209***	0.227	0.293***
	(0.0973)	(0.0980)	(0.0983)	(0.00464)	(0.0157)	(0.0167)	(0.188)	(0.0181)
Main Owner Is Born in the US	0.0150	0.00853	0.00445	0.000698	0.201***	0.250***	0.256***	0.205***
	(0.0699)	(0.0714)	(0.0716)	(0.00159)	(0.00485)	(0.00513)	(0.0830)	(0.00505)
Main Owner's Work Experience	-0.00139	-0.00116	-0.00132	-0.00138***	-0.00663***	-0.00689***	-0.00534	-0.00418***
	(0.00196)	(0.00200)	(0.00198)	(0.0000789)	(0.000224)	(0.000243)	(0.00359)	(0.000221)
State GDP$_{t-1}$	-0.402	-0.518	--	--	-1.796***	-1.195***	--	--
	(0.536)	(0.539)	--	--	(0.000206)	(0.000153)	--	--
Semi-Elasticity of the Interaction Term for a St. Dev. Change in County Inequality	62.85%	73.47%	72.49%	76.21%	-735.36%	-924.59%	-1000.23%	-914.84%
Dependent variable	*Firm Bank and Family Financing*				*Firm Angel and Venture Capital Financing*			
Panel B: County Inequality in 1890								
County Inequality in 1890	0.271	0.416**	0.430**	0.432***	-0.102***	-0.0715***	-0.0128	-0.254***
	(0.214)	(0.201)	(0.196)	(0.00228)	(0.00477)	(0.00406)	(0.418)	(0.00347)
Firm Total Assets$_{t-1}$	0.122***	0.121***	0.123***	0.124***	0.106***	0.112***	0.106***	0.105***
	(0.0118)	(0.0118)	(0.0115)	(0.0000848)	(0.000217)	(0.000185)	(0.0347)	(0.000158)
Firm ROA$_{t-1}$	-0.0185	-0.0206	-0.0213	-0.0214***	-0.107***	-0.107***	-0.110***	-0.107***
	(0.0132)	(0.0130)	(0.0133)	(0.000524)	(0.00119)	(0.00127)	(0.0315)	(0.00159)
Firm Tangibility$_{t-1}$	0.203***	0.195***	0.203***	0.200***	-0.00319	0.0143***	-0.0205	-0.0253***
	(0.0495)	(0.0497)	(0.0488)	(0.00217)	(0.00546)	(0.00498)	(0.0949)	(0.00477)
Firm Number of Owners$_{t-1}$	-0.0118	-0.00966	-0.00574	-0.00368***	0.474***	0.461***	0.478***	0.460***
	(0.0600)	(0.0624)	(0.0601)	(0.000873)	(0.00238)	(0.00233)	(0.0659)	(0.00241)
Main Owner Is Female	-0.0138	-0.0180	-0.0190	-0.0184***	-0.252***	-0.253***	-0.272***	-0.300***
	(0.0497)	(0.0497)	(0.0494)	(0.00276)	(0.00752)	(0.00776)	(0.103)	(0.0103)
Main Owner Is African-American	-0.159*	-0.138	-0.134	-0.139***	0.0360***	0.0129	0.0679	0.156***
	(0.0900)	(0.0912)	(0.0914)	(0.00439)	(0.00983)	(0.0103)	(0.140)	(0.0143)
Main Owner Is Hispanic	0.0363	0.0395	0.0333	0.0246***	0.280***	0.257***	0.220***	0.280***
	(0.0715)	(0.0704)	(0.0694)	(0.00489)	(0.0105)	(0.0119)	(0.0841)	(0.0122)
Main Owner Is Asian	-0.0524	-0.0411	-0.0397	-0.0518***	0.190***	0.206***	0.224	0.304***
	(0.0985)	(0.0981)	(0.0982)	(0.00473)	(0.0158)	(0.0167)	(0.189)	(0.0191)
Main Owner Is Born in the US	-0.00615	-0.0210	-0.0227	-0.0272***	0.215***	0.257***	0.260***	0.208***
	(0.0713)	(0.0740)	(0.0751)	(0.00171)	(0.00491)	(0.00517)	(0.0809)	(0.00512)
Main Owner's Work Experience	-0.00168	-0.00138	-0.00151	-0.00158***	-0.00598***	-0.00573***	-0.00399	-0.00289***
	(0.00200)	(0.00205)	(0.00203)	(0.0000859)	(0.000223)	(0.000244)	(0.00346)	(0.000223)
State GDP$_{t-1}$	-0.342	-0.428	--	--	-1.836***	-1.153***	--	--
	(0.546)	(0.555)	--	--	(0.000212)	(0.000141)	--	--
Semi-Elasticity of the Interaction Term for a St. Dev. Change in County Inequality	33.58%	51.55%	53.29%	53.53%	-73.23%	-51.33%	-9.19%	-182.35%
County Control Variables	No	Yes	Yes	Yes	No	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	--	--	Yes	Yes	--	--
Year Fixed Effects	Yes	Yes	--	--	Yes	Yes	--	--
2-digit Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Year Fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes
Industry*Year Fixed Effects	No	No	No	Yes	No	No	No	Yes
Number of Observations Panel A	6,279	6,242	6,246	6,246	4,328	4,303	4,307	4,307
Number of Observations Panel B	6,242	6,203	6,207	6,207	4,309	4,282	4,286	4,286

NOTES. All Models are estimated with a tobit model left censored at 0 and right censored at 1 and take into account cross-sectional Kauffman Firm Survey weights. The definition of the variables can be found in Table I. *t-1* indicates a one year lag. "Yes" indicates that the set of fixed effects is included. "No" indicates that the set of fixed effects is not included. "--" indicates that the indicated set of characteristics or fixed effects are comprised in the wider included set of fixed effects. Standard errors are clustered at the state level. Standard errors are given in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

TABLE VI

MAIN SPECIFICATIONS EXPLAINING FIRM TYPE

Model	(1)	(2)	(3)
Dependent Variable	*Firm is High Tech*		
Panel A: County Inequality in 2004			
County Inequality in 2004	-0.266**	-0.509***	-0.505***
	(0.103)	(0.144)	(0.147)
Firm Total Assets$_{t-1}$	0.000710	-0.0141***	-0.0144***
	(0.00208)	(0.00280)	(0.00280)
Firm ROA$_{t-1}$	-0.00209	0.00436*	0.00419*
	(0.00195)	(0.00229)	(0.00236)
Firm Tangibility$_{t-1}$	-0.0832***	-0.165***	-0.167***
	(0.0128)	(0.0112)	(0.0112)
Firm Number of Owners$_{t-1}$	0.0356***	0.0167	0.0173
	(0.0126)	(0.0212)	(0.0215)
Main Owner Is Female	-0.0318**	-0.0505***	-0.0512***
	(0.0123)	(0.0141)	(0.0142)
Main Owner Is African-American	0.0466***	0.0352	0.0353
	(0.0142)	(0.0266)	(0.0268)
Main Owner Is Hispanic	0.00221	-0.00767	-0.00757
	(0.0138)	(0.0249)	(0.0250)
Main Owner Is Asian	0.0192	-0.00618	-0.00520
	(0.0269)	(0.0379)	(0.0381)
Main Owner Is Born in the US	-0.0378**	-0.0793***	-0.0785***
	(0.0164)	(0.0273)	(0.0274)
Main Owner's Work Experience	0.00203***	0.00409***	0.00409***
	(0.000324)	(0.000380)	(0.000384)
State GDP$_{t-1}$	-0.0193	0.0806	--
	(0.0875)	(0.149)	--
Semi-Elasticity of the Interaction Term for a St. Dev. Change in County Inequality	-4.25%	-8.13%	-8.06%
Dependent variable	*Firm is High Tech*		
Panel B: County Inequality in 1890			
County Inequality in 1890	-0.111*	-0.159**	-0.159**
	(0.0569)	(0.0670)	(0.0682)
Firm Total Assets$_{t-1}$	0.000597	-0.0142***	-0.0146***
	(0.00209)	(0.00284)	(0.00283)
Firm ROA$_{t-1}$	-0.00221	0.00431*	0.00412*
	(0.00201)	(0.00234)	(0.00241)
Firm Tangibility$_{t-1}$	-0.0853***	-0.169***	-0.170***
	(0.0130)	(0.0113)	(0.0112)
Firm Number of Owners$_{t-1}$	0.0368***	0.0178	0.0185
	(0.0128)	(0.0215)	(0.0218)
Main Owner Is Female	-0.0318**	-0.0501***	-0.0509***
	(0.0123)	(0.0144)	(0.0145)
Main Owner Is African-American	0.0448***	0.0298	0.0301
	(0.0144)	(0.0266)	(0.0268)
Main Owner Is Hispanic	0.000540	-0.0125	-0.0125
	(0.0146)	(0.0231)	(0.0231)
Main Owner Is Asian	0.0224	0.000578	0.00173
	(0.0273)	(0.0381)	(0.0383)
Main Owner Is Born in the US	-0.0363**	-0.0737***	-0.0729***
	(0.0166)	(0.0271)	(0.0271)
Main Owner's Work Experience	0.00205***	0.00415***	0.00414***
	(0.000323)	(0.000390)	(0.000393)
State GDP$_{t-1}$	-0.00910	0.119	--
	(0.0897)	(0.157)	--
Semi-Elasticity of the Interaction Term for a St. Dev. Change in County Inequality	-4.96%	-7.11%	-7.11%
County Control Variables	No	Yes	Yes
State Fixed Effects	Yes	Yes	--
Year Fixed Effects	Yes	Yes	--
2-digit Industry Fixed Effects	Yes	No	No
State*Year Fixed Effects	No	No	Yes
Industry*Year Fixed Effects	No	No	No
Number of Observations Panel A	8,580	8,533	8,540
Number of Observations Panel B	8,523	8,474	8,481

NOTES. All Models are estimated with a linear probability model and take into account cross-sectional Kauffman Firm Survey weights. The definition of the variables can be found in Table I.. *t-1* indicates a one year lag. "Yes" indicates that the set of fixed effects is included. "No" indicates that the set of fixed effects is not included. "--" indicates that the indicated set of characteristics or fixed effects are comprised in the wider included set of fixed effects. Standard errors are clustered at the state level. Standard errors are given in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

TABLE VII

MAIN SPECIFICATIONS COUNTY INEQUALITY 2004 -INSTRUMENTED: FIRM OWNERSHIP, FINANCING AND TYPE

Model	First Stage	(1)	(2)	(3)	(4)	(5)
Dependent Variable	*County Inequality in 2004*	*Firm Equity*	*Firm Is Proprietorship*	*Firm Angel and Venture Capital Financing*	*Firm Bank and Family Financing*	*Firm Is High Tech*
County Inequality in 2004	--	2.605*	3.701*	-0.179	1.627*	-0.0381
	--	(1.593)	(2.034)	(0.393)	(0.873)	(1.260)
Firm Total Assets$_{t-1}$	0.000110	-0.0409***	-0.0534***	0.00181	0.0233***	-0.0127***
	(0.00036)	(0.00342)	(0.00587)	(0.00159)	(0.00275)	(0.00331)
Firm ROA$_{t-1}$	0.000313	-0.0143***	0.0102***	-0.00290***	-0.00182	0.00415
	(0.000267)	(0.00294)	(0.00263)	(0.00106)	(0.00210)	(0.00264)
Firm Tangibility$_{t-1}$	0.000916	0.0833***	0.194***	-0.00402	0.0516***	-0.170***
	(0.00177)	(0.0245)	(0.0300)	(0.00485)	(0.0112)	(0.0122)
Firm Number of Owners$_{t-1}$	-0.000812	-0.00180	-0.358***	0.0492***	-0.00217	0.0176
	(0.00167)	(0.0204)	(0.0466)	(0.0100)	(0.0126)	(0.0236)
Main Owner Is Female	0.000854	0.0134	0.0473*	-0.0115***	0.0151	-0.0528***
	(0.00167)	(0.0222)	(0.0266)	(0.00349)	(0.0138)	(0.0131)
Main Owner Is African-American	0.0116***	0.0887**	-0.00980	-0.00670*	-0.0416	0.0349
	(0.00339)	(0.0359)	(0.0435)	(0.00371)	(0.0254)	(0.0331)
Main Owner Is Hispanic	0.00548	-0.0546*	-0.0205	0.00584	-0.0143	-0.0128
	(0.00354)	(0.0329)	(0.0717)	(0.00995)	(0.0148)	(0.0251)
Main Owner Is Asian	-0.0000599	0.00221	-0.000562	0.00462	-0.0414*	-0.0114
	(0.00373)	(0.0391)	(0.0545)	(0.0128)	(0.0220)	(0.0416)
Main Owner Is Born in the US	-0.00596**	-0.0317	0.0638	-0.00275	-0.0153	-0.0771***
	(0.00281)	(0.0326)	(0.0410)	(0.00509)	(0.0209)	(0.0270)
Main Owner's Work Experience	-0.0000500	0.00139*	0.00144*	-0.0000442	-0.000163	0.00407***
	(0.0000717)	(0.000761)	(0.000767)	(0.000145)	(0.000500)	(0.000360)
State GDP$_{t-1}$	0.0112	-0.396	0.0606	-0.0603	-0.0651	-0.00787
	(0.0228)	(0.253)	(0.198)	(0.0677)	(0.142)	(0.169)
Rain	0.00748*	--	--	--	--	--
	(0.00445)	--	--	--	--	--
Rain Standard Deviation	-0.0157***	--	--	--	--	--
	(0.00535)	--	--	--	--	--
Temperature	0.00102**	--	--	--	--	--
	(0.000447)	--	--	--	--	--
Temperature Standard Deviation	-0.00434***	--	--	--	--	--
	(0.00104)	--	--	--	--	--
Constant	1.749***	-3.526	-8.040**	-0.452	0.304	0.561
	(0.342)	(4.738)	(3.832)	(1.123)	(2.444)	(2.304)
County Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
2-digit Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	No
State*Year Fixed Effects	No	No	No	No	No	No
Industry*Year Fixed Effects	No	No	No	No	No	No
Number of Observations	5,257	5,257	7,199	3,610	5,281	7,203
(Pseudo) R-squared	0.678	0.072	0.300	0.106	0.085	0.119

NOTES. All models are estimated with a 2SLS IV model. The first column contains the results of the first stage regression. *County Inequality in 2004* is instrumented with average division rain fall and temperature between 1895 - 2003 and their corresponding standard deviations. All models take into account cross-sectional Kauffman Firm Survey weights. The definition of the variables can be found in Table I. *t-1* indicates a one year lag. "Yes" indicates that the set of fixed effects is included. "No" indicates that the set of fixed effects is not included. "--" indicates that the indicated set of characteristics or fixed effects are comprised in the wider included set of fixed effects. Standard errors are clustered at the state level. Standard errors are given in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

TABLE VIII

EXPLORING DEMAND AND SUPPLY: MAIN SPECIFICATIONS EXPLAINING COUNTY BANK FINANCING SUPPLY, COUNTY EDUCATION AND EDUCATED COUNTY POPULATION INFLOW

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable	*No. of Bank Establishments per 1,000 Capita*			*County Percentage of Adults with College Degree or More*			*Population Inflow with at least College degree*		
Panel A: County Inequality in 2004									
County Inequality in 2004	-0.806***	-0.971***	-6.579***	-95.993***	-61.234***	-171.166**	-17.121***	-7.237***	-19.955**
	(0.296)	(0.315)	(1.803)	(14.748)	(11.156)	(83.163)	(3.844)	(1.300)	(8.602)
County Population$_{t-1}$	--	-0.111***	-0.130***	--	2.582***	2.260***	--	1.985***	1.955***
	--	(0.014)	(0.015)	--	(0.408)	(0.640)	--	(0.036)	(0.047)
Wage Inequality	--	1.368***	-1.735*	--	56.182***	-12.524	--	5.159***	-1.409
	--	(0.230)	(0.974)	--	(8.030)	(48.054)	--	(1.282)	(4.594)
County Catholic to Protestant Ratio	--	-0.004	-0.029**	--	1.005**	0.514	--	-0.013	-0.121*
	--	(0.011)	(0.014)	--	(0.480)	(0.654)	--	(0.051)	(0.071)
County Personal Income Per Capita$_{t-1}$	--	-0.024***	-0.085***	--	0.424	0.738	--	-0.004	-0.023
	--	(0.007)	(0.031)	--	(0.327)	(1.359)	--	(0.023)	(0.151)
State GDP$_{t-1}$	--	0.084***	0.108***	--	--	--	--	--	--
	--	(0.031)	(0.041)	--	--	--	--	--	--
County Land Area	--	0.010	0.080***	--	-2.007***	-0.635	--	-0.160***	0.008
	--	(0.012)	(0.019)	--	(0.399)	(1.047)	--	(0.052)	(0.115)
County Federal Government Expenditures Per Capita	--	0.000*	0.000**	--	-0.000	0.000	--	0.000	0.000*
	--	(0.000)	(0.000)	--	(0.000)	(0.000)	--	(0.000)	(0.000)
County Nonfarm Establishments Per Capita	--	0.000***	0.000**	--	0.000	0.000	--	-0.000*	-0.000
	--	(0.000)	(0.000)	--	(0.000)	(0.000)	--	(0.000)	(0.000)
Constant	1.182***	1.498***	8.348***	102.468***	24.756	154.091	22.282***	-8.911***	6.157
	(0.256)	(0.388)	(2.275)	(12.872)	(15.298)	(105.659)	(3.340)	(1.747)	(10.875)
Semi-Elasticity for a St. Dev. Change in County Inequality	*-8.23%*	*-9.92%*	*-67.21%*	*-25.63%*	*-16.35%*	*-45.71%*	*-0.57%*	*-0.30%*	*-0.63%*
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations Panel A	15,690	12,376	11,416	3,138	3,094	2,854	2,515	2,487	2,271

Model	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	*No. of Bank Establishments per 1,000 Capita*		*County Percentage of Adults with College Degree or More*		*Population Inflow with at least College degree*	
Panel B: County Inequality in 1890						
County Inequality in 1890	-0.347***	-0.176**	7.456***	-1.693	4.512***	-0.282
	(0.104)	(0.073)	(2.524)	(2.119)	(1.023)	(0.299)
County Population$_{t-1}$	--	-0.105***	--	2.903***	--	2.009***
	--	(0.015)	--	(0.464)	--	(0.049)
Wage Inequality	--	1.591***	--	88.864***	--	8.568***
	--	(0.304)	--	(9.232)	--	(1.441)
County Catholic to Protestant Ratio	--	0.012	--	1.222**	--	0.033
	--	(0.012)	--	(0.527)	--	(0.068)
County Personal Income Per Capita$_{t-1}$	--	-0.016	--	2.586	--	0.267
	--	(0.035)	--	(2.238)	--	(0.247)
State GDP$_{t-1}$	--	0.083**	--	--	--	--
	--	(0.035)	--	--	--	--
County Land Area	--	0.018	--	-2.542***	--	-0.251***
	--	(0.012)	--	(0.504)	--	(0.081)
County Federal Government Expenditures Per Capita	--	0.000	--	-0.000**	--	0.000
	--	(0.000)	--	(0.000)	--	(0.000)
County Nonfarm Establishments Per Capita	--	0.000**	--	0.000	--	-0.000**
	--	(0.000)	--	(0.000)	--	(0.000)
Constant	0.614***	0.405	15.771***	-67.072***	5.702***	-19.355***
	(0.039)	(0.384)	(0.985)	(20.903)	(0.401)	(2.473)
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations Panel B	13,215	10,460	2,644	2,615	2,170	2,151

NOTES. Models (3), (6) and (9) in Panel A are estimated with a 2SLS IV model. All other Models are estimated using OLS. *County Inequality in 2004* is instrumented with average division rain fall and temperature between 1895 - 2003 and their corresponding standard deviations in Model (3), (6) and (9) respectively. The definition of the variables can be found in Table I. *t-1* indicates a one year lag. "Yes" indicates that the set of fixed effects is included. "No" indicates that the set of fixed effects is not included. "--" indicates that the indicated set of characteristics or fixed effects are comprised in the wider included set of fixed effects. Standard errors are clustered at the state level. Standard errors are given in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

TABLE IX

VARIABLE NAMES, DEFINITIONS, AND DATA SOURCES FOR THE EMPIRICAL ANALYSIS OF JUDGES' RULING

Variable Name	Variable Definition	*Source*
Dependent Variable		
Bank Wins	A bank wins a case when it obtained in full what requested to the court, if it was a plaintiff, or a when the request of the opposing party was denied, when it was a defendant.	*WL*
Main Independent Variable		
County Inequality in 1890	The Gini coefficient of the distribution of farm land in 1890 in the county (for counties in Oklahoma the state-level coefficient is used)	*USC*
Control Variables		
Case Characteristics		
Bank is Plaintiff	= 1 if the Bank was a Plaintiff in the case, = 0 otherwise	*WL*
Number of West Headnotes	Number of West Headnotes Subcategories attributed to the trial by the Westlaw Database	*WL*
First Degree Trial Was a Summary Judgement	= 1 whether the first degree trial was a summary judgement, = 0 otherwise	*WL*
Second Degree Affirms First Degree	= 1 if the second degree trial affirms the sentence of the first degree trial, = 0 otherwise	*WL*
Dissenting Judges in the Second Degree Sentence	= 1 if there were any judges dissenting from the second degree sentence, = 0 otherwise	*WL*
More than Four Parties in Trial	= 1 if there are more than four parties involved in the first degree trial, = 0 otherwise	*WL*
Bank Located in the Same State where the Trial takes place	= 1 if the bank is located in the same state where the trial takes place, = 0 otherwise	*WL*
State and County Characteristics		
Length of Judges Term in Office	Number of Years judges stay in office according to the State legislation before facing re-election or re-appointment	*JS*
State has Judicial Partisan Elections	= 1 if in the State judges are electd via Partisan elections, = 0 otherwise	*JS*
County Population	Total county population at year-end	*USC*
County Catholic to Protestant Ratio	Ratio of the total number of Catholics divided by the total number of Evangelicals in the county at year-end 1980, 1990 and 2000	*ARDA*

NOTES. The table defines the variables used in the empirical analysis of judges' ruling, as well as the corresponding data sources used. *t-1* indicates a one year lag is used in the empirical analysis. Data sources include: *ARDA* = Association of Religion Data Archives; *JS* = Judicial Selection.com *USC* = US Census; *WL* = Westlaw.

TABLE X

DESCRIPTIVE STATISTICS FOR THE EMPIRICAL ANALYSIS OF JUDGES' RULING

Variable Name	Number of Observations	Mean	Standard Deviation	10%	Median (50%)	90%
Dependent Variable						
Bank Wins	1,392	0.52	0.50	0	1	1
Main Independent Variable						
County Inequality in 1890	1,392	0.32	0.16	0.18	0.27	0.55
Control Variables						
Case Characteristics						
Bank is Plaintiff	1,392	0.38	0.49	0	0	1
Number of West Headnotes	1,392	7.93	6.57	2	6	16
First Degree Trial Was a Summary Judgement	1,392	0.36	0.48	0	0	1
Second Degree Affirms First Degree	1,392	0.53	0.50	0	1	1
Dissenting Judges in the Second Degree Sentence	1,392	0.08	0.27	0	0	0
More than Four Parties in Trial	1,392	0.21	0.41	0	0	1
Bank Located in the Same State where the Trial takes place	1,392	0.55	0.50	0	1	1
State and County Characteristics						
Length of Judges Term in Office	1,381	5.81	2.12	3	6	8
State has Judicial Partisan Elections	1,392	0.27	0.44	0	0	1
County Population	1,378	0.56	0.59	0.02	0.38	1.82
County Catholic to Protestant Ratio	1,392	0.95	0.81	0.11	0.67	2.19

NOTES. The table provides the number of observations, mean, standard deviation, 10th percentile, the median (50th percentile) and the 90th percentile of all variables used in the empirical analysis.

TABLE XI

MAIN SPECIFICATIONS COUNTY INEQUALITY IN 1890 EXPLAINING JUDGES' RULING

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	*Bank Wins*							
County Inequality in 1890	-0.106	0.065	-0.205	-0.206	-0.194	0.935*	0.959*	0.909
	(0.149)	(0.243)	(0.135)	(0.136)	(0.134)	(0.541)	(0.503)	(0.546)
State Has Judicial Elections * County Inequality in 1890	--	-0.205	--	--	--	--	--	--
	--	(0.302)	--	--	--	--	--	--
State Has Judicial Partisan Elections * County Inequality in 1890	--	--	0.716*	0.715*	0.662*	--	--	--
	--	--	(0.369)	(0.371)	(0.366)	--	--	--
Length of Judges Term in Office * County Inequality in 1890	--	--	--	--	--	-1.098*	-1.123*	-1.078*
	--	--	--	--	--	(0.622)	(0.586)	(0.622)
Bank is Plaintiff	0.044	0.044	0.043	0.040	0.044	0.044	0.105	0.043
	(0.033)	(0.033)	(0.033)	(0.043)	(0.033)	(0.033)	(0.184)	(0.032)
Bank Located in the Same State where the Trial takes place	-0.043	-0.043	-0.043	-0.043	-0.010	-0.044	-0.044	0.273
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.034)	(0.034)	(0.198)
Number of West Headnotes	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
First Degree Trial Was a Summary Judgement	0.045	0.045	0.044	0.044	0.044	0.046	0.046	0.046
	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)
Second Degree Affirms First Degree	0.020	0.020	0.020	0.020	0.018	0.020	0.020	0.019
	(0.033)	(0.033)	(0.033)	(0.033)	(0.034)	(0.033)	(0.033)	(0.033)
Dissenting Judges in the Second Degree Sentence	-0.021	-0.020	-0.020	-0.020	-0.020	-0.019	-0.019	-0.021
	(0.057)	(0.056)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)
More than Four Parties in Trial	-0.127***	-0.127***	-0.127***	-0.127***	-0.125***	-0.128***	-0.128***	-0.126***
	(0.047)	(0.047)	(0.046)	(0.047)	(0.045)	(0.047)	(0.047)	(0.047)
State Has Judicial Partisan Election s*Bank is Plaintiff	--	--	--	0.011	--	--	--	--
	--	--	--	(0.059)	--	--	--	--
State Has Judicial Partisan Elections*Bank Located in the Same State where the Trial takes place	--	--	--	--	-0.124	--	--	--
	--	--	--	--	(0.400)	--	--	--
Length of Judges Term in Office*Bank Located in the Same State where the Trial takes place	--	--	--	--	--	--	-0.064	--
	--	--	--	--	--	--	(0.181)	--
Bank Located in the Same State where the Trial takes place * Length of Judges Term in Office	--	--	--	--	--	--	--	-0.331
	--	--	--	--	--	--	--	(0.212)
County Population$_{t-1}$	-0.009	-0.009	-0.027	-0.026	-0.024	-0.010	-0.009	-0.009
	(0.032)	(0.032)	(0.034)	(0.033)	(0.034)	(0.032)	(0.032)	(0.032)
County Catholic to Protestant Ratio	-0.009	-0.009	-0.003	-0.004	-0.000	-0.007	-0.007	-0.007
	(0.036)	(0.036)	(0.035)	(0.034)	(0.035)	(0.036)	(0.036)	(0.036)
Constant	0.283**	0.281**	0.253*	0.251*	0.211	0.284**	0.285**	0.286**
	(0.138)	(0.137)	(0.142)	(0.140)	(0.141)	(0.136)	(0.137)	(0.137)
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Case Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	1,337	1,337	1,337	1,337	1,337	1,337	1,337	1,337
R-squared	0.157	0.157	0.159	0.159	0.161	0.157	0.157	0.158

NOTES. All models are estimated with a Linear Probability Model. The definition of the variables can be found in Table IX. *t-1* indicates a one year lag. "Yes" indicates that the set of fixed effects is included. "No" indicates that the set of fixed effects is not included. Standard errors are clustered at the state level. Standard errors are given in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.