

The Relationships Between Inequality, Economic
Growth, and Political Control: Explorations Using U.S.
State-level Panel Data, 1969 - 2005

by

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Abstract

This thesis investigates the relationship between economic inequality, income growth, and political control in US states. I find that in the short run, inequality has a significant and robust impact on growth that is robust to a number of different control variables and estimation techniques. I also find that the relationship between inequality is non-linear; a quartic function relating the Gini coefficient to growth is often significant. When other measures of inequality are used in place of the Gini coefficient, they do not exhibit the same relationship with growth. Finally, political control appears to have a significant impact on both growth and inequality. Democratic control increases growth and reduces inequality, while Republican control has the opposite effects.

Introduction

Since the late 1970s, inequality has increased worldwide, both between countries and within countries. In the United States, the income share of the top 0.1% of wage earners more than tripled, increasing to 10.9%; the share of the top 1% doubled, rising to 21.8%, and the Gini coefficient rose by almost 33%, from its lowest value, .36 in 1967, to approximately .47. Despite the rapid growth in inequality in recent history, the economic consequences of increased inequality and, in particular, its effect on economic growth, remain poorly understood. Both cross-country and US state studies have generated conflicting or inconclusive results, and some factors that might explain the relationship between inequality and growth have typically been neglected, including the effects of legislative interference and political decisions, which were considered significant by Kuznets (1955) in his seminal article on inequality.

While economic growth ultimately drives long-term prosperity, growth in the United States over the last 30 years has been almost entirely confined to the top of the income distribution, and largely to the top 1% of income earners. At least in part, the unequal distribution of growth may be viewed as deliberate, a reflection of policies that advantaged top income earners and disadvantaged the lower and middle classes. Whether these policies contribute to growth, and whether increasing levels of inequality are desirable for growth, are key empirical questions which are currently unanswered. Given the social and economic ramifications of increased income disparity, untangling the relationship between inequality and growth is an analytical project with important policy implications.

In this thesis, I analyze the impact of inequality on growth at the state level in the United States from 1969 to 2005, and attempt to determine the extent to which political control at the state level forms, changes, and mediates this relationship. While Bartels (2008) has recently examined this relationship on the national level, no research has yet analyzed the impact of political variables on growth and inequality at the state level. In order to incorporate political variables in the analysis, I create an index that measures the extent to which either political party controls the political apparatus at the state level. This variable, while it does not account for the changing orientation of the major parties over time or across-states, provides some measure of the ability of either political party to implement economic policies and enables me to examine the impact of these policies on inequality and growth. I use a path analysis approach that determines both the direct effect of political control on growth and the indirect effect through the impact of inequality on growth. I find that my political control index is often a significant factor affecting both growth and inequality -- indicating that Democratic control is growth-enhancing, while Republican control is growth-inhibiting. When I calculate the total impact of political control on growth, I find that a switch from Democratic control of the state political apparatus to Republican control decreases growth by as much as .87% in a year.

In addition to the analysis of political variables, this paper expands on previous work by using a variety of statistical techniques (ordinary least squares (OLS), fixed effects, feasible generalized least squares estimation (FGLS), and Arellano-Bond estimation) and control variables to examine the relationship of inequality and growth at the state level in the United States. When I assume the

relationship to be linear, I find a robustly significant and negative impact of the Gini coefficient on economic growth across almost all specifications over time periods of fewer than twenty years. However, over 20 year intervals, the relationship appears to be consistently positive.

This paper also explores potential non-linearities in the relationship between inequality and growth. A non-linear relationship between these two variables has been posited in various cross-country studies by Banerjee and Duflo (2003), and explored to a limited extent by Voitchovsky (2005) and Bjornskov (2008). In my state-level analysis, I find strong evidence of a quartic function relating inequality to growth; this function indicates that up to a certain point, inequality leads to increased growth, but when evaluated at the mean of the Gini coefficient in my sample, I almost always find inequality to have a negative impact on growth. This impact can be quite large over shorter time periods. It decreases over longer time periods, and as with the linear function, often becomes positive in the long run. Voitchovsky explores non-linearities by using multiple measures of inequality -- in the form of the income shares of different parts of the income distribution -- in the same model. When I include the top 1% income share in regressions that also include the Gini coefficient, the top 1% income often shows a positive and significant effect on growth.

My thesis also investigates the observed relationship between inequality and growth changes when several other measures of inequality are used in place of the Gini coefficient. Other measures of inequality -- the Atkinson and Theil indices, the top 10% income share, and the top 1% income share -- rarely display a robustly

significant relationship with growth. When they are significant, however, the direction of their impact is often different from that of the Gini coefficient.

In summary, my analysis yields the following findings:

--political variables have a significant effect on growth directly and indirectly through their impact on inequality,

--Democratic control tends to contribute to growth and reduce inequality, while Republic control reduces growth and increases inequality

--inequality, as measured by the Gini coefficient, reduces growth over time periods shorter than 20 years.

This thesis is structured as follows. Chapter 1 examines theories linking inequality to growth. Chapter 2 discusses measurements of inequality and the empirical research that has been done relating growth, inequality, and political ideology, both at the national and international level. Chapter 3 describes the data and methods I use to conduct my analysis. Chapter 4 summarizes the results of my empirical work, and Chapter 5 concludes by discussing the implications of my results and comparing my results with the results of previous studies.

Chapter 1: A Theoretical Basis For A Relationship Between Inequality, Growth, And Politics

Inequality and Growth

Numerous theories attempt to explain the impact of inequality on economic growth. These theories may be broadly classified as political, economic, and social. In this thesis, I focus primarily on the political and economic theories, and, in the empirical analysis, attempt to determine the impact of political variables on inequality and economic growth. Political and economic theories relating inequality to growth generally fail to agree on the direction of the effect of inequality, and on the mechanism by which the effect is transmitted. In addition, some of the prominent theories relating inequality and growth have been shown to be inaccurate when examined empirically.

Political Theories Linking Inequality to Growth

Inequality has been hypothesized to affect growth through three main political channels. The principal political theories -- rent-seeking, political instability, and fiscal -- all hypothesize an inverse relation between inequality and growth. In the rent-seeking models, increased inequality in income gives the poor an incentive to engage in rent-seeking activities. These activities extract wealth from the economy without improving productivity; rather than conducting transactions or earning profits, the poor manipulate the economic environment to make money. These activities have been shown to be detrimental to investment and growth. In addition,

rent-seeking activities are thought to inhibit the development of institutions important to growth (Alberto Alesina and Roberto Perotti, 1994).

In the political instability model, inequality leads to social unrest, and, in some cases, to violent action to overthrow those in power, thus tending to reduce growth (Alesina and Perotti, 1994). Social unrest is thought to be especially damaging to certain institutions, such as property rights, which have been shown to be especially important for growth (Daron Acemoglu, Simon Johnson, and James Robinson, 2001). However, more recently, Paul Collier's empirical work has shown that inequality has a negligible statistical effect on violent conflicts (Collier, 2007).

In the fiscal models, the most common category in the literature, government decisions and fiscal policy are largely decided by voters, whose votes are primarily determined by personal incomes. Alberto Alesina and Dani Rodrik (1994) focus on the relative share of labor endowment and capital endowment, which they model as monotonically related to the distribution of income, as determinants of voting behavior. All public investment is financed by proportional taxation of capital income, but the increased taxation that accompanies increased government investment leads to reductions in the return to capital, which in turn (assuming the availability of higher returns elsewhere) lowers private capital investment. Higher inequality in resource distribution, especially capital distribution, leads to a lower median income which in turn leads to political demand for high levels of redistribution, because the median voter has little capital and thus little potential for wealth accumulation. While a low rate of taxation that maximizes growth is posited (some money is needed to fund government services that protect rights and ensure

that markets function correctly), when inequality creates demand for redistribution, taxation may rise above the optimal level that maximizes capital accumulation and growth. This excessive taxation rate will quench growth through the blunting of incentives and the distortion of markets caused by the decrease in the marginal product of capital (Alesina and Perotti, 1994). Torsten Persson and Guido Tabellini (1991) and Giuseppe Bertola (1993) also develop variations of this type of model.

Stefan Josten and Achim Truger (2003), however, conclude that the median voter theorem is an inaccurate way of connecting voter preferences, inequality, and redistribution. Josten and Truger break down fiscal models into three components: (1) rising inequality that leads to redistribution, (2) increased distribution that requires financing by increased taxation, and (3) increased taxation that leads to distortions of incentives and reduces growth. They examine each of these links in turn to determine the ability of the fiscal models to describe real world behavior.

If government redistribution is determined by majority rule and voters are self-interested, then voting is likely to be characterized by “collective intransitivity” -- there is unlikely to be one income distribution that will dominate any other among voters. In this situation, the median voter loses importance and is replaced by the group of voters whose voting behavior is thought to be the most elastic. This “probabilistic” voting fails to produce a pattern in the distribution of tax burdens, though it does switch the tax burden to those voters whose preferences are least elastic. To address these analytical complications, the median voter theorem restricts voter preferences to a single dimension -- voters pay attention to only one issue -- and have only one peak in that dimension, meaning that voters have one scenario they

prefer to all others. However, Josten and Truger note that redistribution entails a wide variety of programs and consequences and is anything but a one-dimensional issue; the flexibility and multiplicity of possible redistribution programs means that preferences are likely to have several peaks -- a selfish median voter may want to take income from both the rich and the poor, leading redistribution to be from the tails to the center instead of monotonically increasing. Redistribution programs, moreover, do not affect all voters equally, and change over time. Taxes are used for a variety of different purposes; taxation does not necessarily imply the absence of investment. While wasteful government expenditure may reduce growth, government investment may operate as an engine of growth.

Other problems with the median voter theorem stem from the endogeneity of political participation. Voting rates, access to officials, and political influence increase with income and education, meaning that the median voter may no longer be the decisive voter, and since, given the size of nations, direct democracy is impossible, delegated politicians are subject to lobbying, interest groups, and political bargaining. In addition, economic models assume preferences to be fixed, but it is in the nature of democracy that views change through interactions with fellow citizens as well as politicians; Larry Bartels (2008), *e.g.*, shows the importance of advertising in swaying voters. Voters, moreover, do not vote on taxes, nor do they determine how tax revenue is allocated: representatives vote on tax policies, and these representatives must attempt to satisfy a large group of constituents, with varying degrees of wealth and varying desired taxation levels.

Empirically, rent-seeking models have been largely ignored in the empirical literature that explores the links between inequality and growth. Violent conflict models are likely to apply only in the developing world (if at all), since the threat of violence is fairly low in most developed countries. Econometric studies have largely failed to support the median voter theorem as a channel through which inequality affects growth. The current political connections theorized between inequality and growth seem ill-suited for a study of inequality and growth in the United States.

Economic Theories Linking Inequality to Growth

In addition to the political theories outlined above, several purely economic theories address the impact of inequality on growth. These theories suggest that there might be both positive and negative impacts of inequality on growth. Inequality may have disparate effects through multiple channels on the same part of the distribution.

Neo-classical economics typically associates inequality with incentives -- some inequality is required to provide incentives for labor, so there is a trade-off between equity and growth (Arthur Okun, 1975). In addition, Nicholas Kaldor (1956) suggests that inequality creates incentives for the more productive use of resources; inequality has also been associated with innovation, risk-taking, and entrepreneurship (Voitchovsky, 2005). However, high inequality is thought to limit domestic demand, reducing the potential for industrialization and growth (Kevin Murphy, Robert Schliefer, and Andrei Vishny, 1989). Some economists believe that savings rates change with income level, as posited by John Maynard Keynes (1936). If the rich save a higher percentage than the poor, then redistribution from the rich to the poor will reduce savings and investment. Of course, to the extent growth is a

function of consumer demand and/or of the increased prosperity of laborers, and to the extent the rich spend substantial sums on luxury goods or invest in secondary and unproductive or non-entrepreneurial activities, redistribution from rich to poor will tend to increase growth.

Another frequently discussed link between inequality and growth involves imperfect capital markets. Imperfect information, limited collateral, and poor contract enforcement prevent the poor from accessing capital markets, reducing investment, entrepreneurship, and growth (Debraj Ray, 1993). The inability of the poor to obtain credit is especially detrimental because, as a consequence of their low incomes and diminishing marginal returns, their investments are theoretically more productive than those of wealthier persons (Roland Benabou, 1996b). Benabou also theorizes that the loss in growth and efficiency will be reduced in relation to the level of pre-investment redistribution, and that the growth-maximizing tax rate will increase with the level of inequality.

Phillip Aghion and Patrick Bolton (1993) formalize the mechanisms hypothesized by Debraj Ray (1993) and Benabou, using the capital market as an engine for growth. Inequality is generated because investors do not possess perfect insurance, and investments yield randomized returns; increasing the overall level of societal capital may enable the poor to make investments, increasing their wealth. The model shows that if capital accumulation takes place at a rate above a certain threshold, wealth will “trickle down” from the rich to the poor -- the wealthy will make investments that create jobs and increase wages for the poorer section of the population. However, redistribution policies will make the economy more efficient --

since the poor do not need to borrow as much money to finance investments, their choices are less distorted. The redistribution must be permanent to produce a long term positive impact on societal efficiency.

Abhijit Banerjee and Andrew Newman (1993) model the interplay between occupational choice, income distribution, and economic growth, and also incorporate capital market imperfections. Due to these imperfections, poor people have difficulty borrowing, and are unable to pursue some occupations that require certain levels of investment. They argue that if the ratio of very poor to very rich people is high, development will “run out of steam,” resulting in both low employment and low wages. Conversely, a society with few poor people, even if per capita income is low, will develop rapidly and end up at a high wage, high employment equilibrium. They suggest that their model is more realistic than other models, since it accounts for possible non-linearities in development -- and that accounting for these non-linearities leads to somewhat different policy ramifications. Banerjee and Newman’s model also indicates that a large one--time redistribution will have lasting effects on equality and development.

Social Theories Linking Inequality to Growth

I classify several theories as social theories -- these theories link inequality to growth through education and class prejudice. Perotti (1993) and Benabou (1996a) design models that relate inequality to growth through human capital investment. In addition to human capital theories, Kaushik Basu (2001) examines the way inequality leads to prejudices that stigmatize productive groups. These models generally indicate that inequality reduces overall societal productivity.

Summary of Theories Relating Inequality and Growth

Three classes of theories relate economic inequality and economic growth. Political theories suggest that inequality has a negative impact on growth, but the mechanisms through which inequality interacts with growth are either unlikely to apply in the United States or lacking in empirical support. Economic theory appears to indicate that the effects of inequality on growth largely offset each other: inequality may have a detrimental effect on income growth for those at the lower end of the income distribution -- due to constraints in human capital and an inability to make productive investments -- and a largely positive effect on income growth for those at the higher end of the distribution -- due to increased incentives, productivity, savings, and the ability to make large investments in profitable projects. Social theories generally suggest inequality decreases overall productivity.

The Importance of Politics for both Inequality and Growth

In his seminal paper “Economic Growth and Income Inequality,” Simon Kuznets (1955) was one of the first economists to address the causes and effects of inequality, and the relationship between inequality and economic growth. He discusses a variety of factors that impact inequality and develops a theory that links inequality to growth through a gradual industrialization process. Two of the primary factors he mentions as influencing inequality are legislative interference and political decisions. Kuznets states:

To discuss this complex of processes is beyond the competence of this paper, but its existence and possible wide effect should be noted and one point emphasized. All these interventions, even when not directly aimed at limiting the effects of accumulation of past savings in the hands of the few, do reflect the view of society on the long-term utility of wide income inequalities. This

view is a vital force that would operate in Democratic societies even if there were no other counteracting factors. (9)

Kuznets sees politics as a “vital force” in shaping inequality -- perhaps even the most important factor, since it exists even if the other factors he discusses do not. While empirical investigation of the impact of political variables is beyond the scope of his paper, Kuznets notes that “political decisions” should be “emphasized” in any discussion of the causes and effects of inequality.

Larry Bartels (2008) theorizes that inequality in the United States is directly related to political partisanship, through the policies implemented by the Democratic and Republican administrations. He suggests that partisan differences in both macroeconomic policies -- Democrats follow expansionary policies, focusing on decreasing unemployment and improving growth, while Republicans focus on decreasing inflation -- and microeconomic taxation and transfer policies -- Democrats generally favor more progressive taxes, as well as more robust social service programs -- are among the largest factors effecting inequality. According to his theory, the Democratic combination of improved social services, increased taxation, reduced unemployment, and expansionary policies lead to decreased inequality and increased growth. In contrast, the Republican focus on reducing inflation, cutting government spending (often in the form of reduced social services), and decreasing the progressivity of the tax system creates higher levels of inequality and decreases growth.

Apart from the work of Bartels, political ideology has been almost entirely ignored in the empirical analysis of the impacts of inequality on growth. In cross-country analysis, political institutions are occasionally discussed, but the actions of

governments are ignored -- rather than “emphasized,” as suggested by Kuznets -- with the exception of Bjornskov (2008), discussed below. Papers that use panels of American states do not address political variables in any way. In this thesis, I will build on the suggestion of Kuznets and expand on the work of Bartels, by addressing the impact of politics on the link between inequality and growth at the state level.

Chapter 2: What Do The Data Say? Empirical Work On The Relationship Between Inequality, Growth And Politics

Empirical examinations of the theories that link inequality and growth have been conducted using a number of different countries and over various time periods. Data on inequality are often available only intermittently or only for recent years, and the data are often of questionable quality, even in the supposedly high quality data sets. The infrequency of data and its poor quality often has a marked impact on empirical results, as does the selected measure of inequality and the forms of modeling employed. While empirical studies are inconclusive about the effect of inequality on growth, recent work on the importance of political ideology finds it to be a significant factor in the inequality-growth relationship. In this chapter, I first discuss several different measures of inequality that are used later in empirical analysis, and then summarize examine the results of a number of important cross-country studies of the relationship between inequality and growth and a number of important studies of this relationship within the United States. Finally, I examine the relatively recent empirical work on the impact of political ideology on the inequality-growth relationship.

Measurement of Inequality

There are a number of different ways of measuring income inequality. Some measures, like the percentage of income accruing to each quintile or to the top 1% of all income earners, are simple measures of the concentration of income; the 90-10, 90-50, 50-10 and other ratios express the relations among various parts of the income

distribution. Other measures, such as the Gini, Atkinson, and Theil indices attempt to summarize the entire income distribution. The measures of inequality may have different empirical links with growth; this is of potential importance in attempting to undertake a thorough description of this relationship. This thesis will focus on five ways to measure income inequality. In most research, the Gini coefficient, which reflects the entire spread of the income distribution, is the primary measure used. The Theil index and Atkinson index are occasionally used in the literature. This thesis primarily uses the Gini coefficient to measure inequality, but also includes analysis of the Theil and Atkinson indices, the top 1% income share, and the top 10% income share.

The Gini coefficient collapses the Lorenz curve into a number on a scale measured from 0 to 1. The Gini takes the absolute value of the difference in incomes between every two people in the population and weights it by the probability that those two people would be picked from the population, which is $n_j/n * n_k/n$. Because the income differences are double-counted -- $|Y_j - Y_k|$ is the same as $|Y_k - Y_j|$ -- this summation is then divided by two (Ray, 1993). It is then divided by the mean income to scale the number according to the income of the population, so that populations can be compared:

$$G = (1/2n^2\mu) \sum_{j=1 \text{ to } m} \sum_{k=1 \text{ to } m} [n_j n_k |Y_j - Y_k|]$$

On the scale of the Gini coefficient, 0 represents perfect equality and 1 represents total inequality (Ray, 1993).

A different type of inequality measure is the Theil index, which has two components, a weighted average of inequality within subgroups, and a weighted

average of inequality between subgroups (Conceicao and Ferreira, 2000). The Theil index is calculated by taking the logarithm of the ratio of the subgroup population share to the subgroup's income share, and then weighting the subgroup ratios and adding them. If the ratio is one, the contribution to inequality is 0, because the ratio is equal to one when a subgroup's share of the population is the same as its share of the total income. The Theil index is 0 if the income is distributed perfectly equally and positive when it is not; regional contributions to the Theil index can be either positive or negative.

The Atkinson index translates the Theil index onto a scale of 0 to 1 -- this scale is the same as the scale of the Gini. The Atkinson index is actually a family of indices; different Atkinson indices place different weights (indicated by the value of ε , which represents inequality aversion) on different incomes. When ε is close to 0, this means that there is low inequality aversion, and the index becomes increasingly sensitive to movement in the upper end of income distribution. Conversely, as ε approached 1, inequality aversion is high, and the index is more responsive to changes in the lower end of the income distribution. The Atkinson index used in this thesis has an inequality aversion value of .5. The Atkinson index is calculated using the following formula.

$$A_{\varepsilon}(y_1, \dots, y_N) = \begin{cases} 1 - \frac{1}{\mu} \left(\frac{1}{N} \sum_{i=1}^N y_i^{1-\varepsilon} \right)^{1/(1-\varepsilon)} & \text{for } \varepsilon \in [0, 1) \\ 1 - \frac{1}{\mu} \left(\prod_{i=1}^N y_i \right)^{1/N} & \text{for } \varepsilon = 1, \end{cases}$$

Cross-Country Studies on Inequality and Growth

Numerous cross-country studies have been conducted in an attempt to determine empirically the effect of inequality on growth. These studies typically regress per capita income growth on the Gini coefficient. These studies, which use different data and methods, have failed to produce a consensus. Studies that use pooled OLS techniques have generally found a negative effect, while panel estimation techniques have generally yielded a positive effect. While panel estimators are better suited to working with cross-country data of this nature, the data they use have been suggested to be little better than the data sets used in pooled cross-sectional studies (Atkinson and Brandolini, 2001). In addition, panel studies such as the one performed by Barro (2000) have found that the relationship between inequality and growth is not robust to the use of different control variables, and Banerjee and Duflo(2003), based on the data they examine, find little relationship between inequality and growth.

Before the introduction of a new, higher quality data set by Klaus Deininger and Lyn Squire (1998), studies of the effect of economic inequality on growth were restricted to cross-sectional regression studies. To test their fiscal model, Alesina and Rodrik (1994) use a data set that they refer to as “high quality,” which includes information from 46 OECD countries and developing countries collected by Gary Fields (1989). They also test a larger sample of 70 countries for which they had data. To measure inequality, they use the Gini coefficient for income. To avoid reverse causality -- growth affecting inequality, instead of inequality affecting growth --two stage least squares regression with instrumental variables for Gini coefficients (GDP

in 1960, primary enrollment rate 1960, literacy rate in 1960, infant mortality in 1965, secondary enrollment in 1960, fertility in 1965, and an Africa dummy as instruments) were run over two sample time periods. Alesina and Rodrik controlled for initial per capita income and primary school enrollment, two variables found to be significant in other studies. Alesina and Rodrik's regressions show that income inequality has an individually significant and robust negative effect on economic growth in both democracies and non-democracies. The introduction of a dummy variable for democracy does not affect these results.

Persson and Tabellini (1994) also test the relationship between inequality and growth, hypothesizing that they are connected through the median voter theorem, and obtain results comparable to those of Alesina and Rodrik. They use two samples, a small sample of data from highly developed countries, and a large cross-country sample. Their data come from a data set compiled by Felix Paukert (1973): they have only 56 observations, ranging over roughly fifteen years. Using the portion of total personal income in the hands of the middle quintile of the population as a proxy for equality, and controlling for initial development and education, their model demonstrates that equality has a positive effect on growth. However, in contrast to Alesina and Rodrik, Persson and Tabellini find that this relationship holds only in democracies, and that this difference explains a large portion of the disparity in growth between democracies and non-democracies. Persson and Tabellini's findings are not all robust -- some become insignificant with the introduction of dummy variables for continent.

George Clarke (1995) finds results supporting those of Alesina and Rodrik. Pointing out that Ross Levine and David Renelt (1992) found that many models in the empirical literature are sensitive to the inclusion of other variables related to growth, Clarke runs a variety of regressions with a number of independent variables. Using data from a large, cross-country, secondary data set composed by Robert Summers and Alan Heston (1991), and controlling for initial income per capita, primary enrollment, political stability, and other factors, Clarke employs four different measures of inequality -- the Gini coefficient, the Theil index, the coefficient of variation, and the ratio of the portion of total income earned by the poorest 40% of the population to the portion of total income earned by the richest 20% of the population. Each measure of inequality is found to have a significant and negative effect on growth. Clarke then tests for heteroskedasticity in his error terms and finds that his errors are heteroskedastic. To account for heteroskedastic error, he recalculates his regressions with robust standard errors and recalculates using weighted least squares techniques, and still finds a significant and negative impact of inequality on per capita growth. Like Alesina and Rodrik, Clarke goes on to run two stage least squares regressions with regional dummies and the square of initial GDP per capita as instrumental variables, and his results become even more negative and significant. Finally, Clarke adds even more variables to his initial set of independent variables, and tests the relationship in democracies and non-democracies; his results stay negative, significant, and robust.

In 1998, Deininger and Squire compiled all the data available on income distribution and developed “better and more comprehensive data” by removing

measurements that were either not based on household surveys, obtained from samples unrepresentative of an entire country's population, or the result of incomplete income assessments. Under their new criteria for satisfactory data, much of the data used in early studies was not considered acceptable. With their new data set, Deininger and Squire performed cross-country regressions of inequality on growth, controlling for initial income, investment, education, and a black market premium, and discovered that income inequality "is not a robust determinant of future growth," becoming highly insignificant when regional dummy variables are included. Deininger and Squire argue in favor of abandoning aggregate studies of the effect of inequality on growth in favor of country and policy-specific studies, citing the failure of data to indicate any consistent relationship like the theoretical Kuznets curve.

With Deininger and Squire's new data, studies were performed using more advanced econometric techniques -- fixed and random effects regressions on panel data instead of ordinary least squares regressions on cross-country data -- in order to reduce such econometric problems as omitted variables. A fixed effects regression eliminates all country-specific effects that remain constant over time. Using this new technique with the improved data, Kristin Forbes (2000) finds a positive and significant effect of inequality on economic growth that proves to be robust. She criticizes previous cross-country studies on three points. First, she claims that their estimates of a negative relationship between inequality and growth largely fail to pass tests of robustness. Second, she states that previous studies are subject to measurement error, and suggests that more unequal countries might under-report their inequality data and grow more slowly than similar countries that are more equal,

leading to an increased negative effect of inequality in cross-country estimates (and also omitted variable bias, because the inclusion of regional dummy variables often leads to insignificant variables, the effect of which is hard to predict in a multivariate analysis). However, she does not mention how her work manages to overcome the measurement error problem.

Finally, she notes that the previous studies do not describe how changes in inequality within a country will affect its growth -- this requires panel estimation techniques. Forbes includes education, initial income, male and female human capital, market distortions, and period and regional dummy variables in her regressions. She demonstrates that these results hold under several tests of robustness. Forbes does not propose a possible cause for her results. Hongyi Li and Heng-Fu Zou (1998) use similar techniques and the same data set and reach similar conclusions: while the relationship is often ambiguous, inequality shows a positive and significant effect on growth. They believe this is because equality in the distribution of income leads to higher median income and increased taxation -- lowering growth.

After Forbes (2000), panel studies typically find either a relationship between inequality and growth that is not robust not significant. Robert Barro (2000) uses the Deininger and Squire data set, but adds many observations from studies Deininger and Squire discarded that he considers "fairly comprehensive." Barro performs both random effects panel regressions with growth in GDP per capita as the dependent variable and three stage instrumental variable least squares regressions with the investment to GDP ratio as the dependent variable. Barro has at least one observation

on 84 countries, and 68 countries with two or more observations. He includes investment, fertility, inflation, government spending, and measures of democracy and rule of law as independent variables. His regressions show that Gini coefficients have no significant relation with subsequent economic growth -- perhaps because the various theoretical effects of inequality on growth offset each other. Barro finds that if he omits the fertility rate variable from his regression, he replicates previously obtained results of a negative and significant relationship between inequality and growth. However, he does find that when he splits his sample into developed and developing countries, inequality appears to have a negative effect on growth in poor countries but a positive effect on growth in rich countries. This would also appear to contradict a Democratic mechanism by which inequality leads to more growth, since richer countries are by and large more Democratic than poor ones. Barro suggests that inequality may have a positive effect on growth if investments have large startup costs in comparison to median income, in which case decreasing inequality would also decrease investment. This positive effect may offset the traditionally posited negative effect, leading to a minimal overall effect of inequality on growth. Furthermore, in poor countries, where institutions are less developed, the negative effects are more likely to dominate because loans are more difficult to obtain, and investments are riskier. In wealthier countries with improved institutions, Barro believes that the positive effects of inequality on growth are more important.

Anthony Atkinson and Andrea Brandolini (2001) review Deininger and Squire's data -- the data used by Forbes and Barro -- and conclude that despite its supposed high quality, it is still not entirely accurate or consistent. They analyze the

data from OECD countries, since there are multiple reliable sources of inequality data to compare with the Deininger and Squire data. Using data from the Luxembourg Income Study (LIS), they find that measures of the Gini coefficients in the LIS and the measure in Deininger and Squire only have a correlation of .48. In addition, they note that the Gini coefficient is calculated differently in the United States, where pre-tax income is used, and the United Kingdom, where disposable income is used. Some Gini measures, moreover, are weighted by household, some by person, some use net measures, some use gross measures; the time periods over which the Gini is measured vary from country to country, as do studies conducted to determine inequality -- consumption surveys, expenditure surveys, or household surveys. Atkinson and Brandolini replace the Deininger and Squire data with data from other sources and repeat several econometric studies, including those performed in Romer and Romer (1998) and Barrell and Genre (1999). They come to very different conclusions using different data, both in the level of the variables and in the trend they display.

Atkinson and Brandolini examine 12 different inequality measures from the Netherlands created by different organizations over the last forty years; all of them are markedly different. Similar uncertainty about the correct data measure exists in many of the OECD countries, including England, France, the U.S., and Canada.

To deal with these data problems, Atkinson and Brandolini insert dummy variables, indicating the use of household or personal data, gross or net income, and income or expenditure data. They find that inserting a dummy for income and expenditure data leads to a 6% change in estimated coefficients. However, Atkinson and Brandolini conclude that since the relationship between inequality measures

changes over time, simply inserting a dummy variable does not, in the end, solve the problem of conflicting data sets. They caution against the use of secondary data sets but acknowledge that they have no alternative to propose.

Despite Atkinson and Brandolini's warnings, cross - country studies of the relationship between inequality and growth continue to rely on the Deininger and Squire data set. Abhijit Banerjee and Esther Duflo (2003) determine that the relationship between inequality and growth is not linear, as had been assumed in all previous studies. They find that any changes in inequality are associated with a decrease in future growth rates. The relationship between inequality and the magnitude of changes in inequality is also non-linear, and there is a negative relationship between lagged inequality variables and growth rates. This non-linear relationship explains why numerous studies have yielded different answers using different econometric techniques. Banerjee and Duflo re-derive the theoretical models, including the Democratic models, and show that "there are no strong grounds for thinking that the right specification would be monotonic . . . none of the theories give us any confidence that the effect will be properly identified." Their re-derived theoretical models suggest that fixed effects should be used either to regress the growth rate in period $t+1$ on the change in the Gini coefficient in the previous period, or on the change in the Gini coefficient combined with the current Gini coefficient. Using both Barro's and Perotti's sets of control variables, they find that the past change in inequality squared has a negative and significant effect on the growth rate, while the first degree past change is insignificant. These results remain robust when the current level of inequality is introduced, and hold for both set of control variables.

Duflo and Banerjee also run fixed effects regressions with a lagged Gini variable and a lagged Gini variable squared; these results are insignificant. They conclude by stating that the data say very little about the relationship between inequality and growth, and suggest that microeconomic data is more likely to demonstrate a robust relationship.

In another test of the potentially non-linear nature of the inequality-growth relationship, Sarah Voitchovsky (2005) attempts to determine whether the inclusion of several different smaller sections of the income distribution -- instead of the whole distribution -- changes the relationship between inequality and growth. Using an Arellano and Bond estimator similar to the one used by Banerjee and Duflo (2003), she finds that the Gini, the 90/75 percentile ratio, and the 50/10 percentile ratio are insignificant on their own, but when all are included, are jointly significant. She also finds that the 90/75 ratio and Gini are more jointly significant if the 50/10 ratio is included. In this specification, the 90/75 ratio appears to have a positive and significant impact on growth, while the Gini has an opposite and significant effect. Thus she suggests that a single measure of inequality may be unable to capture the complex and varying relationship between inequality and growth, and inclusion of multiple measures may be necessary.

The cross-country studies of the effects of economic inequality on growth have yielded a variety of conflicting results about both the form and the direction of the relationship. Generally, the use of ordinary least squares estimation yields a negative and robust relationship between inequality and growth, while the use of panel techniques has usually shown either a positive effect or inconclusive results.

However, both the earlier data used in OLS estimation and more recent, supposedly high quality, panel data have been shown to be undesirable for cross-country analysis, casting doubt on the validity of any of the results. Table 1, organized chronologically, summarizes a number of the most important studies -- the authors, data sets, statistical techniques, and conclusions about the connections between inequality and growth.

Table 1 -- Summary of Cross-Country Studies on the Relationship Between Inequality and Growth

Author	Data	Method	Result
Alesina and Rodrik (1994)	Fields (1989), Taylor and Hudson (1972)	OLS, 2SLS	Inequality has a significant negative impact on growth
Persson and Tabellini (1994)	Paukert (1973)	OLS	Inequality has a negative impact -- not robust
Clarke (1995)	Summers and Heston (1991)	OLS, 2SLS, WLS	4 different measures of inequality have a significant negative impact
Deininger and Squire (1998)	Deininger and Squire (1998)	OLS	Income inequality shows a negative effect (not robust, land inequality shows a significant negative impact.
Li and Zou (1998)	Deininger and Squire (1998)	Fixed and Random Effects	Income inequality has a significant positive impact
Forbes (2000)	Deininger and Squire (1998)	Fixed and Random Effects	Income inequality has a significant positive impact
Barro (2000)	Deininger and Squire (1998) + some other data that Deininger and Squire did not include	Random Effects, 3SLS	No robust relationship between inequality and growth.
Banerjee and Duflo (2003)	Deininger and Squire (1998)	Fixed and Random Effects, Arellano and Bond	No robust relationship between inequality and growth.

The table illustrates the wide variety of data sets and statistical techniques that have been used. Even examination of the same data set -- in recent years, Deininger and

Squire's data -- rarely leads to the same conclusions about the relationship between inequality and growth.

Studies of Inequality and Growth in the United States

Ravi Kanbur, in his chapter in Atkinson and Bourguignon's *Handbook of Income Distribution* (2000), discusses several important areas of future study for social scientists who wish to deepen the understanding of the connection between income distribution and economic growth. One of the directions he suggests is a new emphasis on case studies of individual countries. Cross-country studies have many problems; there are a multitude of econometric difficulties, making it difficult to draw policy conclusions, and it is difficult to test alternative hypotheses about development in these studies. Kanbur states:

A superior approach is one which looks at country experiences in their historical and policy detail, and approaches the issues of policy directly and specifically -- relying on cross-country regressions of inequality on per capita income or growth to support or contradict a policy "tradeoff" between the two does not seem to have been very productive. (832)

This corroborates the suggestions by both Banerjee and Duflo (2003) and Atkinson *et al.* (2007) to focus on studies of individual countries.

The United States presents a unique opportunity for an in-depth empirical study of a single country, since it has some of the world's most reliable inequality data available over a long contiguous time period -- most of the 20th century. In addition, the use of state level data provides enough observations to employ more complex regression techniques like the panel estimators or Arellano and Bond estimators used in the cross-country regression analysis. Combining the number of states, the length of time for which data are now available, and the number of

available economic variables, state level analysis provides a very high number of observations compared to cross-country studies with decadal observations, and this increases the accuracy of parameter estimates. While regressions using United States state-level data may avoid some of the problems present in cross-national regressions -- measurement error and parameter variation will likely be reduced -- problems such as multicollinearity and heteroskedasticity will likely still exist, and new potential problems may arise, such as the presence of interstate mobility and regional shocks.

Mark Partridge (1997) performed the first empirical study of the relationship between inequality and growth in the United States using state-level data. He postulates that state-level data may be more desirable as a medium for examining the inequality-growth relationship than cross-country data, because states are more similar than countries -- the great differences that exist across countries in human capital levels, institutions, governments, and other factors that impact inequality and growth may make coefficient estimates unstable and subject to the effects of outliers. He also notes that “states still have great discretion in setting benefit levels” and, based on evidence showing the great variation in payments from different programs, suggests that state economic policy is not overwhelmed entirely by national economic policy. Partridge has decadal observations from 1960 -- 1990 for 48 states, and he uses pooled OLS estimation techniques along the lines of Alesina and Rodrik (1994). Using measures of the inequality in family income before taxation, he regresses growth rates over ten year periods on a variety of control factors measured at the beginning of each ten year period. This lag in control variables (measured in levels) prevents endogeneity, since growth in period $t+1$ cannot impact, for example, human

capital in period t . Partridge includes an assortment of control variables: % graduated high school but not college, % graduated 4-year college, % of state employment in mining, construction, manufacturing, transportation, finance, insurance, real estate, and government, state welfare expenditures, initial state income, regional dummies for the south, west, and midwest, and decadal dummies for the 1970s and 1980s. His industrial mix variable coefficients are measured with respect to the excluded sector, which is traded goods and services.

Partridge's results indicate that the Gini coefficient has a positive and significant effect on the state ten year growth rates, ranging in magnitude from 60.27 in the smallest model to 124.71 in the most complex. He replaces the Gini coefficient with the income share of the middle quintile to test alternative measures of inequality; this specification yields a significant and positive impact of the middle quintile income share on growth. When both the Gini and the middle quintile income share are included, they both remain positive and significant, suggesting that greater range in the income distribution and a larger middle class share of income are desirable for growth. The inclusion of the middle quintile income share increases the magnitude of the coefficient on the Gini variable. Partridge also finds that the Gini has a positive and significant impact on growth over thirty year periods, though the effect is only significant at the 10% level.

Ugo Panizza (2002) finds that the impact of inequality may be negative for fixed effects estimation, though these estimates are not robust. In contrast to Partridge, who used pooled OLS and census data from 1960 -- 1990, Panizza uses a variety of more complicated regression techniques and tax data from 1940 -- 1980

(his data are also measured for the 48 continental states at ten year intervals), and he also uses pre-tax income. Panizza compares the variation in the state level inequality data to the variation present in the cross-country sample used by Perotti (1996); while there is about two-thirds less variation in the state data, Panizza deems this variation sufficient for accurate analysis. He also examines the extent of within-state variation, since this is the variation employed in fixed effects analysis; he finds that there is a large amount of variation in the state income shares of the middle quintile, but a significantly smaller level of variation in the state Gini coefficients. He controls for the same human capital variables as Partridge, but instead of controlling for industry employment, region, and decade, he only controls for the level of urbanization and the % of the population above the age of 65; in addition, he controls for the level of initial income per capita rather than the log.

Using pooled OLS, Panizza finds that the Gini coefficient is negatively and significantly related to growth over ten and twenty year periods. Over ten year periods, the magnitude of the coefficients on the inequality variable is -4.04; over twenty year periods, the magnitude shrinks to -.99. Use of the middle quintile income share again results in a positive but insignificant effect on growth. When fixed effects are employed, and the model is expanded to include decadal dummies, there is a significant and negative relationship over ten year periods for both the middle quintile income share and the Gini coefficient. The magnitude of the Gini here is much greater -- -6.03 and -7.75. Panizza notes that “the inclusion of time dummies exacerbates the multicollinearity problem of the fixed effects estimations; on the other hand, their exclusion is likely to be the cause of omitted variable bias;” an F-test

rejects the null hypothesis that the dummies are jointly insignificant so Panizza chooses to include them. When twenty year time periods are used with fixed effects, regression results indicate no robustly significant impact of the Gini coefficient on growth, though the third quintile income share has a significant and positive effect. Panizza finds some evidence of a quartic relationship between the Gini coefficient and growth, but the relationship is such that the Gini would only impact growth positively if it increased massively. He concludes by noting that while his observed negative relationship is not robust to changes in model specification and time periods examined, he never finds the positive relationship seen in Partridge. However, this may be due to the fact that his data included observations from 1940 and 1950, when inequality was decreasing, whereas Partridge's data begin in 1960, when the decline in inequality was coming to an end. When Panizza experiments with dropping decades in his sensitivity analysis, his results change significantly.

Partridge (2004) focuses on potential differences between the inequality-growth relationship in the short and long term, partially in response to the lack of a significant long-run impact of inequality on growth in the work of Panizza. Partridge states

...because fixed-effect techniques often disregard persistent effects, when used alone, they can lead to misleading results when most of the variation is cross-sectional as is the case for income distribution and institutional features. One conclusion is that the literature is not so paradoxical when allowing that the short- and long-run results may be different and that both overall inequality and the relative well being of the middle class have separate effects.
(2)

Partridge suggests additional advantages to using state data: since states are open economies and have close ties in their economic systems, there will be large flows in

factors of production between states, serving to “magnify how small disparities in initial conditions affect economic growth. . . Hence, any income-distribution/growth relationship should be much easier to detect using states.”

Partridge (2004) tests the model used in his previous paper and the model used by Panizza, and he extends his data through the year 2000. He includes initial income in some specifications, but not in all -- there is some evidence that states, which have been highly integrated for over a century, are near their steady state growth paths, in which case only temporary cyclical or structural shocks cause them to deviate from their growth paths, so their initial income levels should not be included in the analysis. Using Panizza’s specification and pooled OLS, Partridge finds that both the middle quintile share and the Gini coefficient have a positive, significant, and fairly stable (ranging from 100.4 to 164.8) impact on growth over ten year periods and over a significantly longer period of forty years (ranging from 295.5 to 587.1). Random effects estimation yields similar results for ten and forty year time periods. The coefficients are smaller over ten year periods using random effects than they were for pooled OLS, and the coefficients over forty year periods are smaller than their ten year counterparts. A Hausman test indicates that random effects and fixed effects coefficients are different, usually indicating that fixed effects estimation should be employed, but Partridge notes that studies have found this test to be unreliable if any classical assumptions fail to hold. Fixed effects results show that the Gini coefficient has an unstable relationship with growth, positive and significant under several specifications, but negative under others; in addition, the magnitude of the coefficients is unstable over ten year periods. Partridge finds that fixed effects

only uses 15% to 25% of the variation in the Gini coefficient, and suggests that these results are consequentially inaccurate.

Mark Frank (2009) uses a yearly panel data set of pre-tax state level inequality from 1945 -- 2004 in his analysis of state level inequality; this new expanded panel “has both the comprehensiveness and the flexibility to further . . . empirical evaluation.” He also suggests that state data are advantageous due to their homogeneity -- in cross-country studies, structural differences are almost impossible to measure accurately and play a large role in the growth of countries. In addition, he notes that the superior data availability in the U.S. reduces the possibility of omitted variable bias.

Frank uses complex statistical techniques that are not used by previous studies -- different types of dynamic panel error correction estimation. He controls for average wages in ten different industries as well as human capital. He finds that the relationship between the income share of the top decile and economic growth is robustly positive, with a magnitude between .431 and .785, and that this relationship exists mainly due to a specific relationship between the top end of the income distribution and growth. The impact he finds is small; holding other factors constant, a two standard-deviation increase in the income share of the top decile leads to .072% increase in the growth rate. Using other measures of inequality -- the Gini index and Atkinson Index, which attempt to describe the entire income distribution, and the top 1% and top 10% income shares -- still yields a positive relationship, but the magnitude is much smaller, and the results are not always significant. Frank does

not account for non-linearities in the relationship between inequality and growth and uses a different set of control variables than some of the previous analytical work.

As in the cross-country literature, the studies of inequality and growth in the United States do not reach a consensus on the link between inequality and growth. Partridge (1997, 2004) and Panizza (2002) use panels with decadal observations, and come to conflicting conclusions about the impact of inequality. Frank (2009) is the first to use a panel with yearly measurements of inequality; his data show a positive effect of inequality on growth. Table 2, shown below, summarizes the studies discussed in this section.

Table 2 -- Summary of the Empirical Literature on the Relationship Between Growth and Inequality in the United States

Author	Data	Methods	Results
Partridge (1997)	Decadal panel composed of census data from 1960 -- 1990	OLS	Positive impact of both inequality and the middle class income share
Panizza (2002)	Decadal panel of tax return data from 1940 - - 1980	OLS, fixed effects	Negative impact, not robust, at the very least, no positive impact
Partridge (2004)	Decadal panel of census data from 1960 - 2000	OLS, fixed effects, random effects	Positive impact using OLS and random effects, unstable impact using fixed effects
Frank (2009)	Yearly panel from tax return data, extending from 1945 - 2005	Dynamic Panel Estimators	Robust and positive impact of inequality on growth

The table is organized chronologically, and contains the data set, statistical techniques, and conclusions about the relationship between inequality and growth from each study. No studies have used the same data set; the one study that uses a yearly panel data set uses estimation techniques that are not comparable to the techniques used in previous studies.

The Relationship Between Politics, Inequality, and Growth

While Kuznets's original insight about the importance of politics in the inequality-growth relationship has received some attention in empirical studies through the inclusion of variables measuring the extent of democracy or other institutions, the relation among political ideology and partisanship, inequality, and growth has not been widely studied. Princeton political scientist Larry Bartels investigates the connection between partisan politics in the United States and inequality in *Unequal Democracy: The Political Economy of the New Gilded Age* (2008). He writes:

My aim. . . is to refute the notion that the causes of economic inequality in contemporary America “have little tie to government.” Indeed, I suggest that the narrowly economic focus of most previous studies of inequality has caused them to miss what may be the most important single influence on the changing U.S. income distribution over the past half-century -- the contrasting policy choices of Democratic and Republican presidents. (30)

Examining national data, Bartels finds that real income growth of the lower and middle quintile is lower than real income growth of the upper quintile in Republican administrations, and also lags behind the growth of the lower and middle classes under Democratic administrations. Bartels explores a wide variety of explanations for this phenomenon and concludes that it is almost entirely due to policy choices made by Democratic and Republican administrations. Extrapolating from the trends over the second half of the century, Bartels finds that if Democratic administrations had been governing during the whole post-war period, inequality would have steadily declined; in contrast, a constant Republican presence would have increased inequality significantly above its current level.

Bartels builds on the work of Douglas Hibbs (1987), who found that from 1948 to 1978, the ratio of the top 20% of post tax income earners to the bottom 40% declined under Democratic presidents and grew under Republican presidents. Hibbs calculated a 25% decrease in inequality during Democratic administrations, and he found this result to be significant at the 10% level. Bartels finds that over the second half of the century, the 80-20 ratio increased under every Republican president, declined under 4 out of 5 Democrats. The data also showed that in both halves of the post-war era, income growth for the bottom 20% of earners is significantly higher under Democratic administrations than under Republican administrations, even after omitting years of particularly high or low growth, election years, or partisan transition years.

Bartels performs tests to determine whether this trend is the result of switches between Democratic and Republican administrations -- Republicans coming to power and counteracting unsustainable expansionist policies pursued by Democrats, or Democrats reversing policies implemented by Republicans. If changes in partisan control were responsible for the pattern, the data would indicate large changes in growth rates when the administration changed partisan control; however, he finds that differences in average growth rates at all income levels are about twice as large in presidential terms which did not begin with a switch in partisan control as they are in terms with a partisan transition. Furthermore, second-term Republican presidents presided over increases in inequality that are twice as large as first-term Republican presidents. His results suggest that administrations are more able to impact inequality through policy choices as they cement their political control in a second term.

To test whether the observed pattern stems from non-political factors, Bartels uses regression analysis to analyze a variety of other factors, such as chance, oil prices, or labor force participation. He finds that oil prices have same effect on growth at all income levels, and that labor force participation has helped lower income families more than higher income families. Other trends, like education, have been gradual and reasonably steady, and are thus accounted for in his analysis by the inclusion of time trend terms; they are also unlikely to effect marked changes aligned with partisan regime changes.

In a cross-country study of European nations, Christian Bjornskov (2008) argues that the political ideology of the ruling government affects both the likelihood of implementing redistributive policies and the design of the redistributive policies proposed. In addition, Bjornskov points out that ideology will influence the government's perception of the problem of inequality -- left-wing governments, typically tied to labor unions and middle classes, are likely to be more influenced by unequal resource distribution than right-wing parties, which traditionally rely on support from a wealthy elite. Bjornskov runs panel growth regressions, using fixed and random effects and data at five-year intervals from democracies only (since free voting mechanisms are necessary). He measures inequality with the Gini coefficient and indexes the political leanings of ruling governments from -1 to 1, with -1 indicating left-wing government, and 1 indicating right-wing governments. He notes that inequality and political ideology may be highly correlated, leading to multicollinearity issues, but finds only a small correlation between the two.

Bjornskov's regressions show that inequality has a negative impact on growth, but that it is statistically insignificant as an explanatory variable. In contrast, political ideology is strongly significant, and his regressions estimate that a half-point change in the index -- moving from a centrist to a moderately right-wing government -- leads to a half percentage point increase in the growth rate. Once a government passes a point of moderate left-wing policies, moving towards more centrist policies, inequality begins to be positively associated with growth; before that, for very left-wing governments, the association is negative. Bjornskov also finds some evidence for a non-linear relationship, as posited in Banerjee and Duflo (2003) -- a quadratic function relating inequality to growth is significant. He concludes his paper by stating:

With respect to the theoretical considerations following from the present findings, most political economy analyses of the inequality--growth relation posit a crucial role of government in mediating the inequality--growth relationship, yet virtually all do so in a median-voter setting. On a somewhat broader scale, however, there seem to be no good reasons to assume that other economic and political outcomes exist irrespective of the ideology of the government. . . one of the many possible ways forward for the political economy literature may therefore be to relax the assumption that all governments follow similar goals with similar means and thus to allow for the ideology of the government to affect real economic relations. (8)

Like Kuznets and Bartels, Bjornskov finds political ideology is central part to inequality and the inequality-growth relationship.

Kuznets's original observation -- that political ideology is a significant factor in the relationship between inequality and growth -- informs the work of both Bartels (2008) and Bjornskov (2008). Bartels results suggest that partisanship is one of the most important factors impacting inequality and growth. Bjornskov's inclusion of a political ideology index in his regressions causes inequality to be come insignificant -

- the effect of inequality on growth operates through politics. It seems that political ideology is a crucial component for both inequality and growth. In both studies, political ideology is a crucial component of both inequality and growth.

Chapter 3: Data And Methods

Combining recent strands in inequality-growth literature -- a new interest in single country, in-depth case studies and a recognition of the potential importance of politics in the inequality-growth relationship -- I examine the relationship among political variables, inequality, and growth at the state level. This chapter begins by discussing the data I use in my analysis -- income growth, a number of different measures of inequality, and an assortment of control variables. Then I describe my empirical methodology, various econometric difficulties I face, and the techniques I use to test the robustness of the relationship between inequality and growth.

Data

I have a yearly panel data set, spanning the years 1969 -- 2005, of US state data. My panel does not extend beyond 1969 because state level demographic and industrial data is not readily available before this year. The income distribution data are the same as those used by Frank (2009), and includes a variety of different state income inequality measures: the Gini coefficient, Atkinson index, Theil index, top 10% income share, and top 1% income share for the 48 continental states. Frank constructed these measures from pre-tax income obtained from the IRS. Frank notes that the trends in his new state inequality data match the trends observed by Piketty and Saez, both in the aggregate and by individual states, with the exception of Delaware and Oklahoma. To supplement the inequality data of Frank, and to run regressions similar to some of the regressions run by Partridge and Panizza, I also use the middle quintile income share employed in some regressions by Partridge and

Panizza. These data, which exist from 1963 -- 2004, have been compiled by the Russell Sage Foundation.

The measures of inequality are summarized in Table 3, and the correlations between these variables are shown in Table 4. The average value of the Gini coefficient across-states and time is .53; it has a minimum value of .41 and a maximum value of .72. It has the highest standard deviation of any of the measures of inequality except the Theil index, because it is unbounded on the top end. While the mean of the Theil index is comparable (.55) to the mean of the Gini, its minimum and maximum are very different -- it ranges from .13 to 1.41. The mean of the Atkinson index (.21) is significantly lower than the mean of both the Gini and the Theil. The Atkinson is measured on a 0 to 1 scale, like the Gini, but its range is smaller than the Gini's, spanning from .12 to .38. The mean middle quintile share is 22.3% of total income, which is lower than the mean top decile share, 35.6%. Interestingly, the middle quintile share has relatively little variation over this time period -- its standard deviation is .004, which is the smallest of any measure, and it ranges from .18 to .27. From 1969 to 2005, the income accruing to the middle class has been fairly constant. The top decile share has a much higher standard deviation -- .05 -- and has a maximum value of .54, which means that the top 10% of income earners had more than half the income of an entire state. The average top 1% income share is 11.5%, but it goes as high as 27.5%, and has a standard deviation comparable to that of the Atkinson index.

The correlations between inequality measures are rarely above .9. Interestingly, the correlation between the Gini and the Atkinson index is .76, and the

correlation between the Gini and the Theil index is .82-- the Theil index, despite its lack of an upper bound, has a higher correlation with the Gini index than the Atkinson index. The highest correlation between the Gini and another measure of inequality exists between the Gini and the top 10% income share, at around .9. The Atkinson index has a correlation of .9 with the Theil index. The middle quintile share is negatively correlated with all other measures of inequality.

Table 3 -- Summary Statistics for Inequality Measures

Variable	Obs	Mean	Std. Dev.	Min	Max
Middle Quintile	2100	0.223	0.004	0.178	0.269
Atkinson	1900	0.214	0.038	0.117	0.380
Gini	1900	0.526	0.053	0.410	0.716
Theil	1900	0.555	0.203	0.129	1.409
Top 10% Income Share	1900	0.356	0.049	0.270	0.539
Top 1% Income Share	1900	0.115	0.040	0.050	0.275

Table 4 -- Correlation Coefficients Between Inequality Measures

	Middle Quintile	Atkinson	Gini	Theil	Top 10% Income Share	Top 1% Income Share
Middle Quintile	1					
Atkinson	-0.480	1				
Gini	-0.466	0.755	1			
Theil	-0.531	0.902	0.821	1		
Top 10% Income Share	-0.577	0.869	0.903	0.943	1	
Top 1% Income Share	-0.502	0.803	0.845	0.881	0.938	1

The dependent variables in my regressions are growth in per capita income over one, five, ten, and twenty year periods (from $t-n$ to t , where t represents the present year, and n represents the one, five, ten, or twenty year lag). These data were constructed by the Bureau of Economic Analysis (BEA) and allow determination of the effect of inequality on subsequent growth over various time periods. The data also enable me to compare my results with previous cross-country and cross-state

studies, which generally have growth rates measured over five or ten year periods (or longer).

A variety of control variables, similar to those employed in the various econometric specifications by Partridge, Panizza, and Frank, are used in my regression analysis. These include the percent of total state employment in a variety of industries, the percent of the population over 65, the percent of the population that lives in urban areas, the percent of the population that graduates from high school but not college, the percent of the population that graduates college, state spending on welfare, and regional and decadal dummies. State industry statistics were obtained from the BEA and include the percentage of total employment by state for agriculture, mining, construction, manufacturing, transportation, finance, service, government, and trade. These variables account for the different industrial mixes in different states, which may impact economic growth if certain states have significant levels of employment in high growth industries. Agriculture is the excluded sector in regression analysis, so the coefficients on these variables are measured relative to the agricultural sector.

The percent of the population over the age of 65 is taken from the United States statistical abstracts; the percent of the population living in urban areas by state is available decennially in the census -- yearly observations are interpolated assuming steady growth in this variable. These two variables are employed by Panizza and Partridge, but not by Frank. In theory, it seems likely that the percent of the population over 65 will negatively impact growth, since this population is not generally engaged in productive activity. The effect of the percent of the population

living in urban areas is more difficult to predict, but if most of the industry is located in cities, one might expect this variable to have a positive effect on growth. Panizza finds the percent urbanization and percent over the age of 65 variables to be generally positive and significant, though these coefficients often become negative when decadal dummies are included. The two variables are also positive in Partridge, though not significant.

State per capita welfare spending is also taken from the United States statistical abstracts, though data from four years -- 1973, 1979, 1982, and 1989 -- are missing. The missing data are interpolated by taking the average of the levels of welfare spending in the two years around the missing year. Neither Frank nor Panizza include this variable in their empirical analyses. Both Partridge (1997) and Partridge (2004) find it to have a generally negative effect, which corroborates the empirical work on the impact of government spending in cross-country studies. This study uses the log of welfare spending instead of the level.

In some of the regressions, decadal dummies are included for the seventies, eighties, and nineties, in case of decade-specific shocks. The most recent decade is excluded, so the coefficients on these variables are measured relative to the first decade of the new millennium. However, for most of the panel estimation, yearly dummies -- time fixed effects -- are included in the model, and decadal dummies are not used. Regional dummies are used for the south, midwest, and west to control for regional shocks; their coefficients are measured relative to the excluded northeast region.

The human capital data are also from Frank (2009). High school and college graduation rates are not available yearly by state over the entire time period examined in Frank’s paper; Frank constructs them using Barro and Lee’s perpetual inventory method, which employs the decennial observations as well as data on births, deaths, and migration rates, in order to estimate these graduation rates. Frank compares his constructed data to the measured data from recent years, and finds that the high school data are more accurate than the college data, though both are forecasted accurately. In cross-country studies, the human capital variables generally have positive coefficients. In US state studies, Partridge finds college graduation to be consistently positive, but the high school graduation variable sign varies; Panizza finds them both to be consistently positive. In contrast, Frank finds them to be consistently negative, and suggests that this is due to the “temporal trade-off inherent in educational investment” -- by investing in education, one must refrain from engaging in growth-producing activity.

Summary statistics for the principle dependent and independent variables (except political variables, discussed later) are shown in Table 5 below.

Table 5 -- Summary Statistics for Non - Political Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
High School	1926	0.472	0.151	0.167	0.927
College	1926	0.125	0.061	0.030	0.379
%>65	2000	11.689	2.351	0.874	18.600
% Urban	2000	68.750	14.760	32.200	97.980
% Mining	2000	1.1	1.8	0.0	14.5
% Construction	2000	5.6	1.2	0.0	13.6
% Manufacturing	2000	13.8	6.7	0.0	34.1
% Transportation	2000	4.6	1.0	0.0	8.0
% Finance	2000	7.3	1.6	3.4	14.1
% Services	2000	26.8	7.9	12.4	49.9
% Government	2000	16.6	4.1	10.0	49.4
% Trade	1967	19.5	2.8	11.5	24.4
Log Welfare Spending	1900	6.315	1.709	2.773	10.394
Income Growth	1950	0.061	0.032	-0.071	0.341

To analyze the impact of politics at the state level, I gathered data on the party affiliation of the state governor, and the composition of the upper and lower houses of state legislature, since 1968. Using these data I created dummies for Democratic or Republican control of the governorship, and Democratic or Republican majority or supermajority control in both the lower and upper houses. To get a more accurate measure of the control of the state executive branch by a single party, I generated an index ranging from -2.5 -- Democratic control of the governorship, as well as Democratic supermajorities in both the upper and lower house -- to 2.5 -- Republican control of the political apparatus. Governorship and upper house supermajorities are weighted evenly, followed by upper house majorities, lower house supermajorities, and lower house majorities. The correlation between this index and the Gini coefficient is approximately .2, obviating concerns about potentially detrimental high correlation between the two variables. I assume that basic political decisions, such as the ones discussed in Bartels -- setting state taxes, transfers, and other aspects of economic policy -- are relatively constant across the nation for Republicans and Democrats. While this does not take into account the political differences between, for example, southern Democrats and New England Democrats, Bartels does observe that at the national level, party allegiance is the most important factor driving politicians. The index gives an estimate of the extent to which either party controls the state political machine and is able to implement economic policies.

Table 6 below shows the statistics for the political variables. Nebraska is not included in this data, because it has a unicameral non-partisan legislature and does not keep data on the party affiliation of its representatives. The average percentage of

Democrats in the upper and lower houses of state legislatures is startlingly similar -- 57%. The maximum percent of Democrats in both houses is 100, and the minimum is never 0. On average, there are more Democratic governors than Republican ones over this time period. The political control index indicates that political control leans toward the left, but it has a very high standard deviation.

Table 6 - Summary Statistics for the Political Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
% Dems in Upper house	2004	57.3	19.1	8.6	100
% Dems in Lower House	2003	57.4	18.4	12.9	100
Democratic Governor	2050	0.535	0.499	0.00	1.00
Political Control	2030	-0.388	1.530	-2.50	2.50

Methods

Fixed Effects as the Primary Mode of Estimation

In the first portion of the empirical analysis -- an examination of the economic effects of inequality, without regard for political partisanship -- fixed effects is the primary statistical technique employed. However, a variety of statistical techniques and control variables are used to investigate the robustness of the observed relationship and to determine whether the results are data or model dependent. The regression methods used in the analysis include ordinary least squares, feasible generalized least squares, fixed and random effects, and Arellano-Bond estimators (discussed later).

Panel data estimation techniques attempt to minimize omitted variable bias by eliminating time-invariant unobserved factors that affect the dependent variable. Fixed effects regressions are useful if unobserved factors are correlated with

independent variables. The variables are time-demeaned, i.e., the average of each variable over time is subtracted from each individual value of the variable at given t , thus removing any time-invariant factors, since the value of a time-invariant variable will equal its average value over time. A regression is then estimated using OLS on the time-demeaned data. Fixed effects estimation is also known as within estimation, since only the variation within cross-sectional units is employed. If the unobserved effects are uncorrelated with the other regressors, random effects estimation is more accurate than fixed effects, because it also incorporates the variation that exists between cross-sectional units. Random effects estimation uses quasi-demeaned data, subtracting a portion of a variable's time average from each individual value of that variable; the portion is determined by the number of years and the variances of the error terms. Pooled OLS is then used with the quasi-demeaned data. Since data are quasi-demeaned, regressors that are time-invariant will not be lost (Wooldridge, 2009) .

Frank notes that several economists, including Barro, believe that fixed effects should not be used in situations where much of the variation is cross-sectional (between countries or states). However, for his data on inequality -- the data used in this thesis -- he finds that 78% of the variation in the top 10% income share is within the states, as opposed to only 12% between states. In this thesis, I use both fixed and random effects, and compare their results with a series of Hausman tests to determine which estimation technique is more desirable. Fixed and random effects regressions are of the following form:

$$\text{GROWTH}_{(t, t-n), i} = \beta(\text{DISTR}_{i, t-n}) + \theta X_{i, t-n} + \alpha_i + \alpha_t + \varepsilon_{i,t}$$

In this model, the dependent variable is growth in per capita income from $t-n$ to t , where t is the time period and n is the length of the of the independent variables -- either one, five, ten, or twenty years. The i signifies different states. DISTR is a variable which describes the income distribution. X represents a matrix of control variables. The α_i represents the unobserved state fixed effects, and the α_t are year dummies that attempt to capture the effects of any single year shocks that may carry over to subsequent years and create autocorrelation. Thus I will regress inequality and control variables from one, five, ten, and twenty years ago on subsequent one, five, ten, and twenty year income growth rates. This means, for example, that the growth rate from 1980 to 1981 will be regressed on inequality and controls in 1980; and the growth rate from 1980 to 1985 will be regressed on inequality and controls from 1980.

The matrix of control variables builds on the work of Partridge, Panizza, and Frank. My smallest set of control variables -- referred to as model 1 in tables in this thesis -- includes the human capital variables, the percent of the population over 65, and the percent of the population living in urban areas. A larger set of control variables -- model 2 in tables in this thesis -- includes the human capital variables, as well as the percent of total employment by state in industries discussed above (excluding agriculture). Other variables -- initial income per capita, state spending on welfare per capita -- are also used as controls in both the smaller and larger models (these are models 2 and 4 respectively in tables in this thesis).

The DISTR variable is generally the Gini coefficient, which is the most commonly used measure of income inequality. In some models, multiple measures of

inequality are used, as in Voitchovsky (2005). Due to the importance of the income share of the richest 1% of income earners in the development of inequality in the United States, this variable is often included along with a measure of the entire income distribution, in an attempt to determine if the top 1% income share is driving the relationship between inequality and growth. Panizza and Partridge use the middle quintile income share in addition to the Gini coefficient; I also use the middle quintile income share in a few regressions for comparability with their work.

The Atkinson and Theil indices, which measure the overall spread of the income distribution in a different manner than the Gini, as well as the top 1% and top 10% income shares, are also employed as the DISTR variable in some regressions. This will help me determine whether or not different measurements of inequality have similar relationships with growth. Lastly, the DISTR variable will sometimes contain a non-linear function of one of the five measurements of inequality. This will allow me to test for the presence of a non-linear relationship between inequality and growth.

Based on the proximity and interconnectedness of American states, it seems unlikely that state-specific effects are uncorrelated with other regressors, but a Hausman test determines empirically whether fixed or random effects should be employed. The Hausman test compares coefficients between random and fixed effects estimation and tests the null hypothesis that the coefficients are the same. If the null hypothesis is rejected, the coefficients are significantly different, and fixed effects estimation is more accurate than random effects. Using both the small and the large model (models 1 and 3) and all four time periods, fixed effects and random effects estimates are compared, and Hausman tests values are calculated. In every

case, the null hypothesis of similar coefficients is rejected, so it appears that fixed effects techniques produce the most accurate results in the panel estimation.

Robustness Checks and Econometric Difficulties

OLS regressions will be performed to check the robustness of the relationship I observe using fixed effects, and to facilitate comparison with the work of Partridge and Panizza, both of whom rely largely on OLS specifications. OLS regressions will be of the following form:

$$\text{GROWTH}_{i, (t-n, t)} = \alpha + \beta (\text{DISTR}_{i, t-n}) + \theta X_{i, t-n} + \omega R_i + \alpha_t + \varepsilon_{i,t}$$

The variables are defined in the same manner as they are in the fixed effects equation. R contains regional dummies for the midwest, south, and west (the northeast is left out for comparison). These variables are not used in fixed effects regressions because state fixed effects are included.

If the presence of heteroskedasticity is detected in ordinary least squares specifications (through the use of the Breusch-Pagan test) weighted least squares (WLS) or feasible generalized least squares (FGLS) regressions can be used as an alternative method of estimation (along with the use of heteroskedasticity robust standard errors in OLS estimation). When using state data, WLS assumes that the error terms have variances proportional to state population. To account for this when using state data, each variable is divided by the population of the state, and ordinary least squares estimation is used. However, Wooldridge (2009) notes that there are several issues with WLS. WLS does not account for correlation across errors within a state -- which appears highly likely for US state data, since certain shocks will

impact a variety of economic processes within the state -- or heteroskedasticity at the individual level. For this reason, FGLS is used instead of WLS.

In addition to potential problems with non-constant error terms, it is likely that the data will have serial correlation -- errors will be correlated across time, since a shock to a state in one year will have effects over many years. I test for serial correlation by obtaining the residuals from my OLS regressions and regressing them on my dependent variables and the lagged residuals. If the lagged residuals are significant in this regression, this indicates the presence of serial correlation. As noted earlier, the presence of yearly dummy variables in panel estimation accounts for yearly shocks; when OLS estimation is used, I also include these yearly dummies in an attempt to clear out any year-specific shocks that may affect subsequent years.

In the recent empirical growth literature, there is no consensus on the inclusion of initial income levels as a control variable in inequality-growth regressions. In Barro's cross-country growth work, initial income is used as a proxy for initial national development. In this capacity, it has been theoretically suggested and empirically shown to be negatively related to ensuing economic growth (this phenomenon is known as conditional convergence). However, Partridge notes that

. . . both endogenous and neoclassical growth models suggest that initial-income term eventually drops out when economies are near enough to their steady state (limit) growth paths. This suggests the income term can be omitted because when states are very close to their steady-state, deviations primarily reflect transitory cyclical and structural shocks rather than neoclassical convergence" (7).

If initial income is included, but structural and cyclical shocks are the source of deviation from the steady state, Partridge suggests that the initial income coefficient will be negatively biased -- a negative shock would cause a state to grow faster as it

bounces back. Partridge includes initial income in some specifications but not in others; I follow his example.

Another approach that attempts to counteract heteroskedasticity and makes use of panel data estimates the heteroskedasticity function using feasible generalized least squares. In this multi-part technique, the dependent variable is regressed on the independent variables, the residuals from this equation are obtained, and a new variable is created by squaring the residuals and taking the natural log. This variable is then used as the dependent variable and regressed on the independent variables again. From this regression, fitted values are obtained; the weights used in the FGLS regression are calculated by exponentiating these fitted values. Stata extends this technique to panel data, and attempts to account for cross-sectional heteroskedasticity as well as first degree serial correlation.

Again, Wooldridge (2009) suggests that FGLS is problematic. To account for serial correlation, regressors must be strictly exogenous, which is rare (especially in state data, where most economic, political, and social processes are closely connected), and computerized FGLS routines only account for first degree serial correlation (error in time t is correlated with error in time $t-1$), which may not accurately capture the extent of serial correlation. Wooldridge states “. . . it has become more popular to estimate models by OLS but to correct the standard errors for fairly arbitrary forms of serial correlation (and heteroskedasticity). Even though we know OLS will be inefficient, there are some good reasons for taking this approach” (Wooldridge, 428). I use standard errors that are robust to

heteroskedasticity while simultaneously controlling for yearly idiosyncrasies, and I also use FGLS.

In addition to heteroskedasticity and autocorrelation, there are two other econometric difficulties often encountered in this type of empirical analysis: multicollinearity -- high correlation between independent variables -- and endogeneity, which occurs when the dependent variable affects the independent variable, just as the independent variable affects the dependent variable. Kennedy (2008) notes several reasons that multicollinearity can occur:

“ . . . the independent variables may all share a common time trend, one independent variable might be the lagged value of another that follows a trend, some independent variables may have varied together because the data were not collected from a wide enough base, or there could, in fact, exist some kind of approximate relationship among some of the regressors.” (Kennedy, 193)

It is likely in time series data on states that several variables will have similar time trends. It is also possible that variables may have some sort of relationship, since states have been economically and politically connected for hundreds of years. While OLS remains unbiased when multicollinearity is present, the variances of parameter estimates increase, as a result of the lack of individual variation available for parameter estimation. This leads to inaccurate parameter estimation and weak hypothesis testing. There are few ways to combat multicollinearity. Dropping variables that are closely related to other variables, or incorporating more data for additional variation, sometimes reduce the extent of the problem. Partridge, Panizza, and Frank do not mention potential econometric difficulties caused by multicollinearity. In contrast to multicollinearity, simultaneity can be controlled for to some extent. In my model, dependent variables are lagged one, five, ten, or twenty

years -- thus inequality from period t can impact growth in the subsequent one, five, ten, or twenty years, but growth over the subsequent periods can have no simultaneous effect on inequality.

The last statistical technique I employ for robustness is the Arellano and Bond estimator, which is popular in the cross-country growth and inequality literature. Arellano and Bond (1991) developed a generalized method of moments dynamic panel estimator, which was preferable to previous estimators of this type because it did not assume the strict exogeneity of regressors. The Arellano and Bond technique uses lagged dependent variables as instruments in the regression. However, Arellano and Bond note:

An estimator that uses lags as instruments under the assumption of white noise errors would lose its consistency if in fact the errors were serially correlated. It is therefore essential to satisfy oneself that this is not the case by reporting test statistics of the validity of the instrumental variables (i.e. tests of lack of serial correlation) together with the parameter estimates.

While the cross-country literature relies heavily on this estimator, this literature generally only has decadal observations, reducing the potential for serial correlation. Yearly state data have a much higher potential for serial correlation, so it is unlikely that this estimator will be accurate. Arellano and Bond estimates in this thesis consistently indicate first order serial correlation, as well as invalid instrumental variables; however, they are presented to show how different statistical techniques change the observed relationship between inequality and growth.

Path Analysis of the Importance of Political Control in the Inequality-growth Relationship

The second portion of this paper contains a path analysis of the links between political partisanship, inequality, and growth. This analysis employs a system of two equations, one in which growth is the dependent variable, and both inequality and political control are included as regressors (along with the small and large set of explanatory variables discussed before), and a second in which inequality is the dependent variable, and political control is one of the control variables (along with the human capital variables, demographic variables, welfare spending, initial income, and the industrial mix variables). Assuming that the errors in these equations are uncorrelated, which seems reasonable, since almost all the major factors that affect these variables, as well as state and yearly idiosyncrasies, are controlled for -- these two equations can be estimated separately (Wonnacott and Wonnacott, 1990).

When the two equations are estimated separately, political control has a direct effect on growth and an indirect effect that operates through inequality. The total effect can be calculated by multiplying the coefficient on the political control variable (in the equation in which inequality is the dependent variable) and the coefficient on the inequality variable (in the equation in which growth is the dependent variable) and then adding this to the direct effect of political control (the coefficient on this variable in the equation in which growth is the dependent variable). Both equations are estimated using fixed effects (with both state and year effects).

Chapter 4: Results

Estimation Without Political Variables

OLS

While fixed effects is my primary method of estimation, I initially use ordinary least squares estimation, in order to compare the results with those of previous papers that use state data and OLS techniques. I begin using model 1 and regress income growth from $t-1$ to t on the Gini coefficient from $t-1$. I include yearly dummy variables in an attempt to account for autocorrelation from year-specific shocks that influence subsequent years. This regression results in an insignificant coefficient on the inequality variable. However, when initial income and the top 1% income share are included in regression analysis, the Gini has a negative coefficient, significant at the 5% level, with a magnitude around $-.067$.

The initial regression passes the Ramsey specification test and a test for serial correlation, but the errors appear heteroskedastic based on a Breusch -- Pagan heteroskedasticity test. Thus all models discussed here are estimated using heteroskedasticity robust standard errors. Later, other attempts are made to address heteroskedasticity. The addition of initial income, welfare spending, and the top 1% income share causes the Gini coefficient to become significant, but it also causes the model to fail the Ramsey specification test. It is possible that non-linearity is causing this functional form misspecification; this is also addressed in subsequent regressions.

The college graduation variable is consistently significant, with a positive impact on growth that increases when the top 1% income share is included. Regional dummies show little significance. Initial income shows a negative impact on growth;

initially it is only significant at the 5% level, but it becomes significant at the 1% level when the top 1% income share is included. The coefficient on the welfare variable is not significant. The top 1% income share shows a positive and significant impact on growth that is constant in magnitude across several specifications. The inclusion of initial income and the top 1% income share causes the negative magnitude of the coefficient on the Gini variable to increase. Adjusted r-squared values are around .63; all regressions have 1778 observations. Table 7, shown below, contains a sample regression output; all of the results are reported in the appendix, which is available from the author upon request.

Table 7 -- OLS Regressions of Growth on the Gini Coefficient and the Small Set of Control Variables (Lagged 1 Year)

VARIABLES	Model 1	Model 2
Gini	-0.0151 (0.0247)	-0.0675** (0.0336)
High School	0.0103 (0.0131)	-0.00983 (0.0135)
College	0.0553** (0.0242)	0.138*** (0.0321)
%>65	0.00026 (0.00017)	0.00028* (0.00017)
% Urban	-8.86e-05* (4.64e-05)	-5.91e-05 (5.60e-05)
Midwest	-0.00118 (0.00150)	-0.00078 (0.00150)
South	0.00353*** (0.00126)	0.00164 (0.00130)
West	0.00131 (0.00129)	-0.00019 (0.00154)
Initial Income Per Capita		-1.20e-06*** (3.46e-07)
Log Welfare Spending		-0.00021 (0.00055)
Top 1% Income Share		0.134*** (0.0397)
Constant	0.0465*** (0.0131)	0.0888*** (0.0181)
Observations	1778	1778
Adj. r-squared	0.636	0.640

Robust standard errors in parentheses, year dummies included but not shown
 *** p<0.01, ** p<0.05, * p<0.1

I conduct a Variance Inflation Factor test with the most basic model specification to see if multicollinearity is an issue. A VIF test calculates the factor by

which the variance of a coefficient is higher due to correlation with other regressors.

VIF tests are calculated as follows:

$$VIF_j = 1/(1 - R_j^2)$$

Where R_j^2 is the r - squared value obtained when variable X_j is regressed on all the other regressors and an intercept. The high school and college graduation variables are highly correlated, as expected, with VIF values around 13.5. The only other variables with a VIF value above 10 are initial income and the top 1% income share. If 10 is taken as the threshold for problematic multicollinearity, as suggested in Wooldridge, this indicates that standard errors will be larger, making inference more difficult. Estimates will remain unbiased in the presence of multicollinearity.

OLS regressions of growth over five year periods on inequality and the basic set of control variables display no relationship between the Gini coefficient and growth. The college graduation variable is significant at the 1% or 5% level and has a positive effect, as seen previously. Initial income continues to have a highly significant and negative impact on growth. The top 1% income share has a positive effect on growth that is significant at the 5% level; it has an annualized effect on the growth rate around .048. The Midwest regional dummy is always significant with a negative coefficient. The number of observations for this set of regressions is 1680, and adjusted r-squared values are approximately .85.

Like OLS regressions with control variables lagged one year, OLS regressions of ten year growth rates on the small set of control variables yield a negative effect of inequality on growth only when the top 1% income share is included. The college graduation variable is uniformly significant at the 1% level, with the same effects

observed in regressions with smaller lags. The percent of the population that lives in urban areas is marginally significant in a few specifications for the first time. Both the West region dummy and the Midwest region dummy have negative and significant impacts; this may indicate that over these longer time periods, neglected regional factors and time shocks have more impact. The inclusion of the initial income per capita variable -- which has a negative effect significant at the 1% level -- and the top 1% income share causes the Gini variable to become significant, with an annualized impact on growth of $-.024$. This is approximately half the size of the annualized effect on growth over one year periods. The top 1% income share is also significant at the 1% level and has an annualized effect of approximately $.1$ on the growth rate; this effect more than outweighs the negative effect of the Gini coefficient. This set of regressions has adjusted r-squared values between $.92$ and $.93$; 1440 observations are available.

Over twenty year periods, the Gini coefficient shows a robustly positive impact on growth, with an annualized effect on the growth rate ranging from $.013$ to $.019$. The college variable continues to be significant; for the first time, the high school graduation variable is significant. Its effect is negative when initial income is included in analysis. The percent of people over the age of 65 becomes significant and negative in all specifications; this may be due to the fact that many people over the age of 65 at the beginning of the time period have died twenty years later. The percent of people living in urban areas also becomes consistently significant -- with a positive impact when initial income is included. The Midwest and West region dummies remain significant. Initial income and welfare spending both display

negative and highly significant coefficients. For the first time, the top 1% income share is not statistically significant. 960 observations are available for these regressions. These regressions have adjusted r-squared values between .94 and .95.

Following the work of Partridge and Frank, a larger model that includes a variety of variables that reflect the composition of state industry is also estimated over various time periods using OLS. However, all variations of this larger model consistently failed both the Ramsey specification test and the Breusch-Pagan heteroskedasticity test. All models discussed here are thus estimated using heteroskedasticity robust standard errors. A test for autocorrelation indicates that it is not a concern as long as yearly dummy variables are included.

Over short time periods (controls lagged one year), the Gini coefficient exhibits the same behavior it did when the small set of control variables was used -- it has a significant negative effect on growth when the top 1% income share is included. The magnitude of this effect is approximately -.12. The college variable is again significant when initial income is included. Of the industrial employment percentages, only construction and service are consistently significant; relative to agriculture, they both have negative coefficients. Again, the Midwest region has a significant and negative coefficient. Initial income per capita is significant with a negative impact, the top 1% income share shows a positive impact that is significant and around .18 in magnitude. Again, the positive size of the coefficient on the top 1% income share is greater than the negative size of the coefficient on the Gini variable. Adjusted r-squared values are similar to the adjusted r-squared values

obtained using the small set of control variables; however, the number of observations available drops from 1778 to 1745 -- some industrial data are missing.

Again, the Gini coefficient displays negative impact on growth when the top 1% income share is included and control variables are lagged five years. The magnitude of this effect is less than half as large as it is over one year periods, decreasing too approximately $-.05$. Construction remains significant with the same effect it had when lagged one year; the services variable becomes insignificant, while the variable measuring employment in trade becomes significant with a negative coefficient. Initial income has a negative and significant effect on growth, and its inclusion causes the college graduation variable to be significant with its usual sign. The welfare spending variable is significant with a small and negative effect. The top 1% income share is also significant, with an annualized impact of approximately $.08$ on growth -- more than counteracting the negative effect of the Gini coefficient. There are fewer observations available when industrial data is used relative to the regressions using the smaller set of controls. Adjusted r-squared values are roughly $.86$.

Using the larger set of control variables lagged ten years, the Gini's behavior remains the same. It has a significant impact when the top 1% income share is included in analysis with a small annualized impact on growth slightly above $-.01$; this is dwarfed by the significant positive impact of the top 1% income share, which above $.05$. 1410 observations are available, and adjusted r-squared values are above $.9$.

Just as the impact of the Gini is robustly positive when lagged twenty years for the small set of control variables, it becomes robustly positive when the large set of control variables is lagged twenty years. Interestingly, the top 1% income share is significant when included with the industrial mix variables; its effect is negative for the first time, but it does not outweigh the positive impact of the Gini -- the net impact of inequality on growth still appears to be positive. 940 observations are employed and adjusted r-squared values are as high as .96.

Table 8 summarizes the annualized impacts of the Gini coefficient on growth obtained using OLS. Throughout this section, the four models discussed in the previous chapter will be shown in tables. Model 1 contains only the Gini coefficient, human capital variables, demographic variables, and time dummies as controls. Model 2 adds initial income, the log of welfare spending, and the top 1% income share to the set of controls employed in model 1. Model 3 contains the Gini coefficient, human capital variables, and the industrial mix variables; while model 4 again adds initial income, the log of welfare spending, and the top 1% income share to model 3. This terminology will be used throughout my thesis. In addition, I specify quartic models; for example, model 1 (quartic), indicates that the set of control variables contains those in model 1 and a quartic function relating inequality to growth.

Table 8 - Annualized Impact of the Gini Coefficient on Growth in OLS Specifications

Lag	Model 1	Model 2	Model 3	Model 4
1 Year	-0.015	-0.068**	-0.033	-0.121***
5 Year	0.009	-0.021	-0.021	0.047***
10 Year	0.000	-0.024***	0.012	-0.020**
20 Year	0.013***	0.018***	0.028***	0.047***

Robust standard errors
 *** p<0.01, ** p<0.05, * p<0.1

Since previous empirical work indicates that there may be a non-linear relationship between economic inequality and economic growth, I explore that possibility using OLS and both my models. Using the smaller model and lagging variables one year, a 4th degree polynomial function of the Gini appears to be significant at the 1% level; the 1st and 3rd terms have positive signs, and the second and fourth terms having negative signs. The quartic function is relatively constant regardless of the explanatory variables included; when evaluated at the mean value of the Gini coefficient, it has a large negative impact on growth, causing a decrease of nearly 10%. The top 1% share is insignificant in these specifications. The quartic terms do little to increase the adjusted r-squared values of these regressions relative to other regressions run over one year periods, which remain around .63. The human capital variables exhibit the same patterns as they did in OLS regressions without non-linear terms -- the high school graduation variable is insignificant while the college graduation variable is positive and significant. The percent of the population over the age of 65 is positive and marginally significant. The observation number is still 1778.

This same quartic function is almost always significant when control variables are lagged five, ten, and twenty years -- when evaluated at the mean value of the Gini, the impact of this quartic function on growth is negative, except when variables are lagged twenty years, and its effect becomes positive. The human capital variables also display the same behavior over the longer time periods. Both the top 1% share and welfare spending are almost always significant. The top 1% share has a negative impact over five year periods (a yearly impact of -.078), but a positive and significant

one over longer periods, with a yearly impact of .134 over ten year periods that shrinks slightly to .098 over twenty year periods. Welfare spending consistently shows a negative effect. Observation numbers are the same as linear regressions, and adjusted r-squared values continue to mirror the r-squared values of similar previous regressions (that lacked non-linear terms).

For the larger model, results again display a significant quartic function relating inequality to growth. This function has alternating signs, a positive first term, and is negative when evaluated at the mean value of the Gini coefficient for all lag periods shorter than twenty years. Over one and five year periods, the Gini has a large negative impact on growth, which is as high as -13%. Initial income and welfare spending are significant (except for initial income over very short time periods), and they have negative coefficients. The top 1% share has a negative impact on growth over the two shorter lag periods, though it is generally insignificant or fails to remain significant when initial income or welfare spending are accounted for; it shows a positive and significant effect on growth over longer periods. The magnitude of this positive effect jumps markedly when initial income is included. When initial income and welfare spending are included in regression analysis, the top 1% income share has a yearly impact of .152 on the growth rate when lagged ten years; when lagged twenty years, the yearly impact is .089. Adjusted r-squared values continue to increase from around .55 for regressions over one year periods to around .9 for regressions with variables lagged ten and twenty years. Tables 9 and 10 below summarize the size and significance of the top 1% income share -- both when included in the small and large models, and when included in with a quartic function

of the Gini -- as well as the quartic functions of the Gini when evaluated the mean Gini value.

Table 9 - Annualized Impact of the Top 1% Income Share on Growth in OLS Specifications

Lag	Model 2	Model 4	Model 2(quartic)	Model 4(quartic)
1 Year	0.134***	0.181***	0.049	0.091*
5 Year	0.047***	0.080***	-0.023	0.028
10 Year	0.096***	0.109***	0.047***	0.075***
20 Year	-0.015	0.046	0.019	-0.047***

Robust standard errors
 *** p<0.01, ** p<0.05, * p<0.1

Table 10 - Quartic Functions Evaluated at the Mean of the Gini Coefficient in OLS Specifications

Lag	Model 1(quartic)	Model 2(quartic)	Model 3(quartic)	Model 4(quartic)
1 Year	-0.098***	-0.063***	-0.131***	-0.102***
5 Years	-0.080***	-0.015***	-0.081***	-0.082***
10 Years	-0.058***	-0.039***	-0.019**	-0.030
20 Years	0.008***	0.047***	0.020***	0.040***

Robust standard errors
 *** p<0.01, ** p<0.05, * p<0.1

Panel Estimation

Fixed effects estimation of the smaller model, using one year lags, shows the Gini coefficient to have a negative and significant impact on growth. The magnitudes of the coefficients are between -.09 and -.15, which is larger than the effect observed when using OLS. Neither the human capital variables nor the demographic variables are significant. The coefficient on the top 1% income share is positive and marginally significant when welfare and initial income are accounted for, with a magnitude of .152 -- almost exactly the opposite of the coefficient on the Gini. Welfare itself is insignificant, while initial income has negative effect, and it is marginally significant. The amount of variation explained by fixed effects regressions is similar to the amount explained by OLS (around .64 when adjusted for number of regressors). This is somewhat surprising since fixed effects only looks at

the within panel variation, and traditionally has lower adjusted r-squared values than ordinary least squares. A sample of fixed effects regression results are shown below in Table 11; the rest are contained in the appendix.

Table 11 -- Fixed Effects Regressions of Growth on the Gini Coefficient and the Small Set of Control Variables (Lagged 1 Year)

VARIABLES	Model 1	Model 2
Gini	-0.0936*** (0.0232)	-0.154*** (0.0442)
High School	8.76e-05 (0.000220)	-0.00011 (0.00021)
College	0.00027 (0.00065)	0.00078 (0.00065)
%>65	0.00034 (0.00026)	0.00034 (0.00026)
% Urban	-0.00028 (0.00023)	-0.00024 (0.00020)
Initial Income per Capita		-8.66e-07* (4.45e-07)
Log Welfare Spending		0.00079 (0.00094)
Top 1% Income Share		0.152* (0.0788)
Constant	0.118*** (0.0254)	0.147*** (0.0273)
Observations	1778	1778
Adj. r-squared	0.639	0.642

Robust standard errors in parentheses, state and year fixed effects included but not shown
*** p<0.01, ** p<0.05, * p<0.1

The Gini coefficient also displays a significant effect when lagged five years. The Gini retains its negative sign; the top 1% share displays a positive sign again, but it is not significant. The coefficient on the inequality variable is both larger -- the annual effect on the growth rate ranges from -.057 to -.064 -- and significant in comparison with the coefficients obtained using OLS. When lagged ten years, the Gini coefficient is only marginally significant in one specification, with a negative impact. As in the OLS regressions, the addition of the top 1% share makes the Gini coefficient significant. However, the top 1% variable is not significant on its own. When initial income is added, the Gini coefficient becomes insignificant again; the top 1% income share becomes significant at the 5% level, with a strong positive

impact on growth. The annualized effects of the Gini on the growth rate are comparable to the impacts observed using OLS, ranging from $-.0206$ to $-.0203$. When initial income, welfare spending, and the top 1% income share are included, the top 1% income share increases growth by approximately $.113$, more than counteracting the negative impact of the Gini coefficient. The adjusted r-squared values hover around $.86$; they rise above $.9$ for regressions with ten year lags.

As in the OLS results, the Gini coefficient exhibits a positive and significant effect on growth when lagged twenty years in fixed effects regressions. The top 1% income share appears negative and significant in most specifications. The top 1% income share rises in magnitude when initial income and welfare spending are added; these variables are both significant, with negative coefficients. The explanatory power of these regressions is again above $.9$. The magnitudes of the coefficients on the Gini are comparable in size and direction -- ranging in yearly impact from $.023$ to $.046$. The yearly impact of the top 1% is $-.025$, but in this case it is more than counteracted by the positive effect of the Gini.

The use of the larger model and fixed effects also yields a consistently negative impact of the Gini coefficient on growth until control variables are lagged twenty years. The coefficient on the Gini variable is almost always larger than in comparable OLS regressions. As in OLS regressions, the magnitude of the Gini's impact increases when initial income, welfare spending, and the top 1% income share are included in the model; the magnitude of the Gini's impact steadily decreases with the length of the time lags and switches signs when the variable is lagged twenty years. When lagged one, five, and ten years, the top 1% share has a positive

coefficient that is significant; it becomes negative and significant over twenty year periods. Initially, it has an annualized impact on the growth rate of .164, when variables are lagged five years, this impact decreases to .094; it rises to .115 when controls are lagged ten years, and then decreases to -.028 over twenty year periods. The magnitude of the Gini exceeds the magnitude of the top 1% income share (when initial income and welfare spending are included in analysis) for all lag lengths except ten years. Initial income is usually significant, with a negative coefficient, for lags longer than one year. Adjusted r-squared values are comparable to OLS and small model fixed effects regressions. The coefficients on the Gini are summarized below.

Table 12 - Annualized Impact of the Gini Coefficient on Growth in Fixed Effects Specifications

Lag	Model 1	Model 2	Model 3	Model 4
1 Year	-0.094***	-0.154***	-0.114***	-0.190***
5 Year	-0.064**	-0.057*	-0.072**	-0.107***
10 Year	-0.024	-0.021	-0.022	-0.048***
20 Year	0.023**	0.045***	0.019**	0.039***

Robust standard errors
 *** p<0.01, ** p<0.05, * p<0.1

Non-linear terms are also then included in fixed effects regressions. Using the smaller model and one, five, ten, and twenty year lags, a quartic function of the Gini coefficient, with a positive sign on the first term, is almost always significant. This function is not significant when control variables are lagged ten years and initial income is included, but an F test of joint significant fails to reject the null hypothesis that the coefficients on the 2nd, 3rd, and 4th degree terms are equal to zero. Again, evaluating the quartic function at the mean value of the Gini indicates that inequality has a negative impact on growth when variables are lagged less than twenty years. Over a one year period, none of the human capital variables are significant, but over five, ten, and twenty year periods, the college graduation variable is often significant.

The coefficient on high school graduation is always negative. The coefficient on college is negative for time periods greater than one year unless initial income is included; in this case, the college graduation coefficient becomes positive, retaining its significance. Initial income consistently shows a negative and significant impact in all specifications with lags longer than one year. The top 1% income share appears to have a generally insignificant impact on growth for all time periods shorter than twenty years, and then a negative and significant impact over the twenty year period; when variables are lagged twenty years and initial income is included, the single year growth impact of the top 1% income share is -.031. The welfare variable is almost always negative, but not often significant. Adjusted r-squared values remained similar to OLS adjusted r-squared values.

In contrast to both the smaller model fixed effects regressions with non-linear terms and the larger model OLS regressions with non-linear terms, the quartic relationship between inequality and growth is largely insignificant in the larger model when fixed effects are employed. The quartic terms are marginally significant when controls are lagged one year and initial income is excluded from the model, and an F-test rejects the null hypothesis that the 2nd, 3rd, and 4th degree terms are equal to zero. In regressions lagging the control variables five, ten, or twenty years, most of the quartic terms are insignificant. An F test on regressions for all these longer periods shows that the null hypothesis (that the coefficients on the polynomial terms were not different than 0) can not be rejected. The coefficient on the top 1% income share, when initial income and welfare spending are included in regression analysis, is consistently positive over one, five, and ten year periods, but it is only significant

over ten year periods, with a yearly impact of .104 on growth. Over twenty year periods, the top 1% income share is negative and highly significant, with an impact of -.031 on the growth rate. The high school variable again shows a consistently negative impact (except over one year intervals), and the college variable again becomes positive and significant when initial income is included (except over one year intervals). Adjusted r-squared values are slightly above those of the smaller fixed effects polynomial regressions. The size and significance of the coefficient on the top 1% income share, as well as the magnitudes of quartic functions of the Gini when evaluated at the mean, are shown below in Tables 13 and 14.

Table 13 - Annualized Impact of the Top 1% Income Share on Growth in Fixed Effects Specifications

Lag	Model 2	Model 4	Model 2(quartic)	Model 4(quartic)
1 Year	0.152*	0.164***	0.041	0.080
5 Year	0.049	0.094***	-0.035	0.063
10 Year	0.011***	0.115***	0.060	0.010***
20 Year	-0.025***	-0.028**	-0.031**	-0.031***

Robust standard errors
 *** p<0.01, ** p<0.05, * p<0.1

Table 14 - Quartic Functions Evaluated at the Mean of the Gini Coefficient in Fixed Effects Specifications

Lag	Model 1(quartic)	Model 2(quartic)	Model 3(quartic)	Model 4(quartic)
1 Year	-0.138***	-0.143***	-0.166*	-0.114
5 Years	-0.118**	-0.036**	-0.064	-0.061
10 Years	-0.058**	-0.031	-0.028	-0.035
20 Years	0.025***	0.065***	0.036*	0.043**

Robust standard errors
 *** p<0.01, ** p<0.05, * p<0.1

Testing Robustness to Other Statistical Techniques

Arellano -- Bond Estimation

A variety of other statistical techniques are employed in order to test the robustness of the observed relationship. The use of Arellano - Bond estimation illustrates the tendency of the impact of inequality on growth to change -- usually

when variables are lagged more than five years -- when different statistical techniques are used. Year dummies are included in this estimation to account for serial correlation. Inequality again shows a robustly negative and significant impact on growth when the Gini is lagged one year -- this appears to exist in both the smaller and larger models. The magnitude of this impact ranges from -.111 to -.162 in the smaller model, and from -.120 to -.198 in the larger model (again comparable to fixed effects results, generally larger than OLS results). When non-linear terms are included, the significant one year effect of the Gini coefficient disappears. Over longer time periods, without non-linear terms, inequality typically displays a positive and significant impact for both the large and small models. The inclusion of quartic terms generally results in no significant relationship with growth, though sometimes the quartic function is significant over longer time periods. However, the 3rd degree term of the polynomial is omitted in regression analysis because it is collinear. This only happens in Arellano-Bond estimates, so the $Gini^3$ term must be collinear with the lagged dependent variable that is included in these estimations. The sign of the top 1% income share fluctuates, and it is inconsistently significant.

The use of Arellano - Bond estimation, as noted earlier, relies on the absence of serial correlation and the validity of the chosen instrumental variables (lagged values of the dependent variable). Since data in cross-country panels are generally spaced ten or more years apart, serial correlation is not a problem; tests reveal that first degree serial correlation is a problem in every Arellano - Bond estimation that I performed (but second degree correlation is not). In addition, tests reject the validity of the instruments employed. The Arellano - Bond estimator appears poorly suited to

yearly panels, but it serves to illustrate how the observed relationship between inequality and growth is dependent on the statistical technique used to estimate over time periods longer than a single year. Important coefficients are displayed below in Tables 15 and 16.

Table 15 - Annualized Impact of the Gini Coefficient on Growth in Arellano - Bond Specifications

Lag	Model 1	Model 2	Model 3	Model 4
1 Year	-0.111***	-0.157***	-0.124***	-0.198***
5 Year	0.024***	0.072***	0.011	0.042***
10 Year	0.015**	0.022*	0.013***	0.004
20 Year	0.003	0.035***	0.011	0.032***

Robust standard errors
 *** p<0.01, ** p<0.05, * p<0.1

Table 16 - Annualized Impact of the Top 1% Income Share on Growth in Arellano - Bond Specifications

Lag	Model 2	Model 4	Model 2(quartic)	Model 4(quartic)
1 Year	0.220**	0.057	0.122	0.122
5 Year	-0.048***	-0.032*	-0.065**	-0.029
10 Year	0.033	0.051**	0.029	0.052***
20 Year	-0.006	-0.006	0.008	-0.010

Robust standard errors
 *** p<0.01, ** p<0.05, * p<0.1
 Quartic results not reported since they are generally insignificant

FGLS Estimation

Another way to account for heteroskedasticity (in addition to the use of heteroskedasticity robust standard errors) is to perform feasible generalized least squares estimation. FGLS controls for both error correlation between cross sectional units (states) and error correlation across time -- yearly dummies are not included in this estimation since it makes a built-in correction for autocorrelation. Using FGLS, the impact of the Gini coefficient is almost uniformly significant and negative (it is insignificant in two specifications for the five year lags). The size of the coefficients obtained using FGLS estimation are sometimes smaller than their OLS and fixed effects counterparts, but there is no consistent pattern. The signs of the human capital

variables vary by specification and the length of the time period; they are often consistent, but no pattern appears. The top 1% share has significant impact over all time periods; it has a positive impact of .09 when lagged one year, a negative impact when it is lagged five years (around -.06 per year) and a positive and significant impact for when lagged ten years (around .08 per year) and twenty years (around .05 per year). In all specifications, the magnitude of the coefficient on the top 1% income share exceeds the magnitude of the coefficient on the Gini. Welfare shows a consistently negative and significant effect on growth.

The use of FGLS and the smaller model (models 1 and 2) again shows the presence of a highly significant quartic relationship, with a positive sign on the first term and alternating signs on subsequent terms. This function appears negative when evaluated at its mean. The top 1% income share is often significant; the direction of its impact is similar in size and direction to its linear counterparts. The human capital variables are again somewhat unpredictable, though often significant: the coefficient on the high school graduation variable is most often negative, and the coefficient on the college graduation variable is usually positive, but sometimes becomes negative when initial income is accounted for. The inclusion of initial income also makes the percent of the population over the age of 65 significant in some instances; it is always negative over one year periods. Welfare appears to have a negative and significant impact in all specifications. I attempted to run the FGLS routine on the larger model, but Stata was unable to perform the estimation when panels were unbalanced. A summary of the FGLS results is included in Tables 17 - 19 below.

Table 17 - Annualized Impact of the Gini Coefficient on Growth in FGLS Specifications

Lag	Model 1	Model 2
1 Year	-0.072***	-0.071***
5 Year	-0.092***	-0.002
10 Year	-0.043***	-0.012***
20 Year	-0.025**	-0.012**

Robust standard errors
 *** p<0.01, ** p<0.05, * p<0.1

Table 18 - Annualized Impact of the Top 1% Income Share on Growth in FGLS Specifications

Lag	Model 2	Model 2(quartic)
1 Year	0.090	0.041***
5 Year	-0.058**	-0.061***
10 Year	0.081***	0.079***
20 Year	0.050***	0.047***

Robust standard errors
 *** p<0.01, ** p<0.05, * p<0.1

Table 19 - Quartic Functions Evaluated at the Mean of the Gini in FGLS Specifications

Lag	Model 1	Model 2
1 Year	-0.086***	-0.133***
5 Years	-0.111***	-0.013***
10 Years	-0.020***	-0.002***
20 Years	-0.005	0.001

Robust standard errors
 *** p<0.01, ** p<0.05, * p<0.1

Other Measures of Inequality

While the majority of empirical analysis related to economic inequality relies on the Gini coefficient, the empirical analysis is also performed using four other measures of inequality: the Atkinson index, the Theil index, the top 1% share, and the top 10% share. For the sake of comparison, OLS regressions (with yearly dummy variables) are estimated as well as fixed effects regressions with state and time dummies. When all the control variables from the smaller set are lagged one year, only the Theil exhibits a significant impact on growth. In contrast to the effect of the

Gini coefficient on growth, the effect of the Theil is positive. If control variables are lagged five years, no other measure of inequality has a significant impact on growth. Over ten year periods, all measures except the top 1% income share have significant and negative impacts on growth, with annualized impacts on the growth rate ranging from approximately -.01 (the Theil) to approximately -.05 (the Atkinson). The rates are comparable to the rates obtained using the Gini coefficient and OLS, though the effect of the Gini coefficient was only significant if the top 1% income share was also included in OLS regressions. As the lag length is extended to twenty years, all alternative measures of inequality become significant, and they all exhibit negative signs. The annualized impacts on growth are similar in size to the impacts obtained when lagging variables ten years. The alternative measures of inequality have adjusted r-squared values comparable to the r-squared values of OLS regressions that use the Gini.

If the larger set of control variables is used, both the Theil and the Atkinson index have significant and positive impacts on the growth rate when lagged one year. The Atkinson index has an effect approximately four times larger than the effect of the Theil. As the lag length is extended to five and ten years, no measure of inequality is significant at the 5% level. Over longer lags of twenty years, all the measures are significant except the top 1% income share, with annualized effects on the growth rate ranging from -.016 (the Theil) to -.051 (the Atkinson).

As with the Gini coefficient, all OLS specifications except for two -- the most basic model, using the Atkinson index as a measure of inequality, and the most basic model with non-linear terms and the Theil index included -- failed the Ramsey

specification test. These two models also fail the Ramsey test when they are examined over longer time periods, and when initial income or welfare spending are included. There is thus evidence of some sort of functional form misspecification in ordinary least squares estimation.

I also explored the possibility of a non-linear relationship between alternative measures of inequality and the growth rate. Using the small set of control variables, the Atkinson index displays a marginally significant quartic function that remains marginally significant over one, five, and ten year periods. The sign pattern on this quartic is opposite to the pattern obtained using the Gini. Starting when variables are lagged five years, the top 10% income share also appears to be related to growth by a 4th degree polynomial function; this function is significant at the 5% or 1% level and exhibits the same sign pattern as the Atkinson index quartic. If lags are extended to twenty years, the Theil index displays a significant quartic relationship with growth that has the same signs as the relationship observed with the Gini coefficient. However, none of these quartic relationships are robust over all four lag lengths. Similar results are obtained when the large set of control variables is used, although fewer quartic functions are significant. The results of regressions using other measures of inequality are shown below in Table 20 and 21.

Table 20 - The Annualized Impact of Other Measures of Inequality on Growth in OLS Specifications

Lag	Theil, Model 1	Theil, Model 3	Atkinson, Model 1	Atkinson, Model 3	Top 1, Model 1	Top 1, Model 3	Top 10, Model 1	Top 10, Model 3
1 Year	0.014*	0.020***	0.049	0.080**	0.030	0.044	0.034	0.049
5 Year	-0.002	0.002	-0.028	-0.011	-0.004	-0.014	-0.011	0.00
10 Year	-0.010***	-0.001	-0.050***	-0.016	-0.006	-0.036*	-0.030*	-0.003
20 Year	-0.017**	-0.016***	-0.061***	-0.052***	-0.020*	-0.012	-0.025***	-0.019***

Robust standard errors
 *** p<0.01, ** p<0.05, * p<0.1

Table 21 - The Annualized Impact of Other Measures of Inequality on Growth in Fixed Effects Specifications

Lag	Theil, Model 1	Theil, Model 3	Atkinson, Model 1	Atkinson, Model 3	Top1%, Model 1	Top1%, Model 3	Top10%, Model 1	Top 10%, Model 3
1 Year	0.019**	0.022***	0.073	0.081*	0.020	0.007	0.035	0.029
5 Year	-0.006	0.002	-0.060	-0.009	-0.016	0.002	-0.048	-0.007
10 Year	-0.016*	0.00	-0.077**	-0.010	-0.011	0.025	-0.073**	-0.013
20 Year	-0.020***	-0.012***	-0.069***	-0.036***	-0.015	-0.011	-0.046***	-0.024**

Robust standard errors in parentheses
 Quartic results not reported since they are generally insignificant
 *** p<0.01, ** p<0.05, * p<0.1

Middle Quintile Income Share

In order to compare the results in this paper with the work of Panizza (2002) and Patridge (2004), I included the middle quintile share of income in some regression analysis using panel estimators. In these regressions, the middle quintile share is not significant except over twenty year time periods, where it has a positive effect -- as does the Gini. The coefficient on the middle quintile share is much larger than the coefficient on the Gini.

I also include the middle quintile income share in fixed effects estimations with yearly dummies. When control variables are lagged one year, the middle quintile share has an insignificant effect on growth in both the large and small models. Over five year periods, the middle quintile share has a large negative impact significant at the 1% level. At first, the coefficient on the middle quintile share is only slightly larger than the coefficient on the Gini, but when initial income is included in analysis, the size of the coefficient on the Gini decreases markedly, while the size of the coefficient on the middle quintile income share increases by a factor of five. However, in the large model, the middle quintile income share remains insignificant. When controls are lagged ten years, the middle quintile income share is

highly significant, with a large negative effect, if industrial mix variables are excluded from the model. When control variables are lagged twenty years, the middle quintile income share is only significant in one specification and displays a large positive effect. These results are not shown since the middle quintile income share is not usually significant.

Summary: The Impact of the Gini Coefficient and Alternative Measures of Inequality on Growth

Linear Relationship

When the relationship between inequality and growth is assumed to be linear, it appears that the Gini coefficient generally has a negative and significant impact on income growth over time periods shorter than ten years, though this is not always robust to changes in the control variables or in the estimation technique. Over ten year periods, the variable is typically insignificant; over twenty year periods, it is generally significant with a positive effect. In contrast to the weakening robustness of the relationship between the Gini and growth over time, the relationship between other measures of inequality and growth seems to grow more significant as lags extend to ten or twenty years; in addition, the effect of alternative measures of inequality over these longer periods is typically negative.

When control variables are lagged one year, the Gini coefficient has a significant and negative effect that is fairly robust across a variety of statistical techniques and different sets of control variables. The magnitude of the impact of the Gini coefficient is also comparable across statistical techniques -- usually in the range of -.1 to -.2 -- though it is higher on average for fixed effects and Arellano - Bond

techniques than for OLS and FGLS techniques. If the Gini increases from its minimum value in the data (around .41) to its maximum (around .71) in a single year, magnitudes in this range would lead to 3 -- 6% decrease in the growth rate. The addition of initial income, welfare spending, and the top 1% income share in both models 1 and 2 generally increases the observed magnitude of the coefficient on the Gini. When the Gini is replaced by alternative measures of inequality, the only significant impacts on growth are positive. However, only one of the alternative measures of inequality -- the Theil index -- has a significant effect robust across specifications and models. The effect of the Theil is much smaller in magnitude than the effects generally seen with the Gini coefficient.

Extending the duration of the lag on the control variables to five years did little to affect the generally robust negative relationship between the Gini coefficient and per capita income growth, except in Arellano - Bond estimations, where the Gini displayed a positive and significant coefficient. The yearly effect of the Gini on growth is on average between -.04 and -.06; if the Gini were to increase by .3 in a year, this would affect the income growth rate by -1.2% to -1.8% in a year. Over 5 years, this amounts to a decrease in growth of about 6% - 9%. When alternative measures of inequality are substituted for the Gini coefficient, no measure has a significant effect on growth.

As all control variables are lagged ten years, the robustness of the relationship between inequality and income growth weakens. While the effect remains robustly negative in FGLS estimates, few specifications estimated with OLS or fixed effects show a significant relationship. Again, the Gini coefficient has a positive and

significant impact in Arellano - Bond regressions. The average effect of the Gini is usually between $-.04$ and $-.02$ (and Arellano - Bond estimates are positive, as noted before). No alternative measure has a significant effect that is robust to different controls and statistical techniques. The occasional significant effect is negative, as are most of the observed significant effects on the Gini.

The previously observed robustly negative relationship between inequality and growth switches to one that is robust and positive as variables are lagged twenty years. The Gini displays a positive and significant effect in OLS, fixed effects, and Arellano - Bond estimates. The size of this effect is around $.02 - .03$. The impact of the Gini remains negative and significant in FGLS specifications. While alternative measures of inequality generally failed to show a robustly significant effect over shorter time periods, the Atkinson index, Theil index, and top 10% income share all show a robustly significant negative impact on growth over twenty year periods. *The Importance of the Top 1% Income Share*

When lagged one year, the top 1% income share is significant in some fixed effects specifications, and most OLS specifications. In OLS estimation, the inclusion of the top 1% income share makes the Gini coefficient significant. When the top 1% income share is significant, its magnitude is often positive and above $.15$, usually larger than the negative impact of the Gini coefficient (though not always). The top 1% share ranges from $.05$ to around $.28$ -- if, for example, the magnitude of the coefficient on this variable is $.15$, then a yearly increase of the top 1% share from its minimum to its maximum would increase growth by around 3.5%.

When lagged five years, the top 1% share is significant more frequently. It is not robustly significant in fixed effects estimations, but it is fairly consistently significant in Arellano - Bond, FGLS, and OLS estimations. The direction of its effect depends on the statistical technique used, and the annualized impacts on growth decrease. In most instances the top 1% income share and the Gini coefficient have opposite signs (for example, the top 1% income share has a negative sign in Arellano-Bond regressions, but when lagged five years, the Gini has a positive effect; the reverse is true in OLS estimates).

As the lag length of the control variables increases, the top 1% income share becomes more robustly significant. Over ten years, the variable is consistently significant across all techniques -- OLS, FGLS, fixed effects, and to a lesser extent, Arellano - Bond. The effect of the top 1% income share is always positive, and its positive size generally overwhelms the negative and significant impacts of the Gini coefficient discussed earlier. When lagged twenty years, the top 1% income share is again inconsistently significant across different estimation techniques: when it is significant, it continues to decrease, negate, or overwhelm the effect of the Gini.

The Non-Linear Relationship Between Inequality and Growth

A quartic function relating inequality to growth is often significant across time periods, control variables, and statistical techniques. This function is always robustly significant in OLS regressions, significant in all fixed effects regressions run with variations of the smaller model, and significant in all FGLS regressions except when variables are lagged twenty years. In addition, the observed quartic always has a positive first term and alternating signs. When evaluated at the mean value of the

Gini coefficient, the quartic has a negative effect on growth for all time periods shorter than twenty years. This effect can be quite large when variables are lagged one and five years, and it decreases gradually over time, until it becomes positive. When alternate measures of inequality are used in place of the Gini, a non-linear relationship is sporadically significant, and is never robust to different sets of control variables over all four time periods.

Estimation with Political Variables

To test the importance of political factors at the state level in the relationship between growth and inequality, political variables reflecting the composition of state houses and the party in control of the governorship (either individually or combined, as in the index discussed earlier) are included in the regressions. Separate regressions were run with growth and inequality as the dependent variables, thus allowing me to determine not only if political variables are important with respect to growth and inequality individually, but also whether these variables exert an indirect effect on growth through inequality.

Effects of Political Control on Growth

I add my political control index as a regressor in equations where growth is the dependent variable. I use fixed effects with yearly dummies and heteroskedasticity robust standard errors in an attempt to account for both heteroskedasticity and autocorrelation. I examine only one and five year periods, since significant political changes are likely to occur over longer periods due to

election cycles, allowing for the implementation of different policies and obscuring the impact of political control.

When lagged one year, the political control variable is significant in every specification. The magnitude of the coefficient ranges from $-.00075$ to $-.00092$ in the smaller model and from $-.00078$ to $-.00087$ in the larger model. Since the index is constructed so that 2.5 indicates firm Republican political control (super majorities in both houses of the legislature and control of the governorship), and -2.5 indicates firm Democratic control, the sign of this coefficient means that Democratic control has a positive effect on growth and Republican control a negative impact on growth. The Gini retains the negative sign and significance it had in previous fixed effects regressions when political control was not included. Lagging the political control index five years causes the variable to become insignificant.

When a quartic function relating inequality to growth is included, political control again appears to have a negative effect when lagged one year (indicating that Democratic control increases growth, and Republican control decreases growth). This effect is significant at the 1% level, with a magnitude ranging from $-.00115$ to $-.00124$ for the small model, an impact slightly larger than the linear result. The significance of the quartic relationship between growth and the Gini is unaffected by the inclusion of the political control index. This is also observed if variables are lagged five years, though the political control variable is only significant at the 10% level, instead of the 1% level seen previously. The size of the effect of control on growth is between $-.00056$ and $-.00066$, roughly half the size of the one year effect. The same pattern is also seen when the larger model is used. All subsequent tables

contain the results of fixed effects estimations; the tables contain the percentage impact of the political variables on the dependent variable (as opposed to presenting the coefficient, as in previous tables).

Table 22 - Annualized Impact (in %) of the Political Control Index on Growth

Lag	Model 1	Model 2	Model 3	Model 4
1 Year	-0.075**	-0.092***	-0.079*	-0.087**
5 Years	-0.032	-0.043	-0.038	-0.040

Robust standard errors
 *** p<0.01, ** p<0.05, * p<0.1

Table 23 - Annualized Impact (in %) of the Political Control Index on Growth in Quartic Model

Lag	Model 1(quartic)	Model 2(quartic)	Model 3(quartic)	Model 4(quartic)
1 Year	-0.115***	-0.124***	-0.109***	-0.116***
5 Years	-0.056*	-0.066**	-0.048*	-0.050*

Robust standard errors
 *** p<0.01, ** p<0.05, * p<0.1

I also use three individual variables -- the percentage of Democrats in the upper house, the percentage of Democrats in the lower house, and a dummy indicating whether or not the governor is a Democrat -- in the regression analysis. In the linear specification, none of these variables is significant if lagged one year. When lags are extended to five years, the percentage of Democrats in the lower house becomes marginally significant with a positive impact on growth. The magnitude of this effect, which is around .05, is the largest impact exhibited so far by any of the political variables used in regression analysis, and it changes little when the quartic function is included. When the quartic function is included in analysis of the small model over one year periods, the governor dummy is significant at the 10% level; it displays a positive effect, indicating that a Democratic governor leads to higher growth. The magnitude is around .0017; however, the significance disappears when welfare spending is accounted for in the regression model. In the larger model, none

of the individual political control variables are significant over one year periods. Again, when lagged five years, the percentage of Democrats in the lower house appears to have a significant and positive effect on growth in both the large and small models.

When the political control index is included as a regressor in non-linear models, I observe a robustly significant and negative impact of this variable on growth. Lagging the political control index five years causes the significance of this effect to disappear. When political control is included in fixed effects regressions that include a non-linear model -- a quartic relationship between the Gini and growth -- the negative coefficient is significant whether or not the variable is lagged one or five years. The effect of this variable is small, from -.00075 to -.00124. Other measures of political control appear largely insignificant when used as dependent variables in growth equations. The percentage of Democrats in the lower house is robustly significant at the 10% level across control variables when a quartic model is included in analysis, and its effect is around .06. This effect is large, and again indicates that Democratic control has a positive effect on growth. Results obtained using individual political variables are shown below in Tables 24 and 25.

Table 24 - Annualized Impact (in %) of Other Political Control Variables on Growth in Quartic Model (Variables Lagged 1 Year)

	Model 1	Model 2	Model 3	Model 4
% Dems in Upper House	2.84	3.24	-1.33	-0.94
Democratic Governor	-0.19	-0.08	0.10	0.11
% Dems in Lower House	5.61*	5.88*	6.41**	6.19*

Robust standard errors

*** p<0.01, ** p<0.05, * p<0.1

Linear results not shown since they were consistently insignificant

Table 25 - Annualized Impact (in %) of Other Political Control Variables on Growth in Quartic Model (Variables Lagged 5 Years)

	Model 1(quartic)	Model 2(quartic)	Model 3(quartic)	Model 4(quartic)
% Dems in Upper House	3.30	3.26	-1.03	-0.68
Democratic Governor	0.11	0.23	0.21	0.23
% Dems in Lower House	5.01*	5.74*	6.24**	6.38**

Robust standard errors

*** p<0.01, ** p<0.05, * p<0.1

Linear results not shown since they were consistently insignificant

Effects of Political Control on Inequality

I use a measure of inequality as the dependent variable to determine the impact of political control on inequality. As explanatory variables, I include the human capital variables, a measure of political control, the demographic variables (percent of the population over the age of 65 and percent urbanization), industrial mix variables, yearly dummies, welfare spending, and sometimes lagged income growth. When the Gini coefficient is the dependent variable and one year lags are examined, political control has a positive impact that is significant at the 5% level. The magnitude of this effect varies between .00144 and .00151. The lagged income growth variable is insignificant in these regressions. The human capital variables both appear to have a negative impact on inequality, which is expected; the percent of the population above 65 has a negative effect on inequality, which may be counterintuitive, since a greater number of older people, who are retired, would likely increase the disparities in income. Similarly, the percent of people living in urban areas shows a positive coefficient (though insignificant), while traditionally higher levels of people living in cities leads to a greater dispersion of income. The only significant industrial variable is manufacturing, which appears to decrease inequality.

Welfare spending has a positive and highly significant coefficient, indicating that it increases income inequality -- this also contradicts the traditional views on welfare spending. As lags are extended to five years, the significance of the political control variable increases and the coefficient remains positive, decreasing in magnitude to a yearly impact around .0003. Manufacturing and welfare spending stay significant and retain their previous signs; the two demographic variables now have their expected signs, but neither of them is significant. Lagged income growth becomes marginally significant.

When three individual variables are substituted for the political control index, only the percentage of Democrats in the upper house is significant, and the sign of its coefficient is negative -- the more Democrats in the upper house, the lower the level of the Gini coefficient. The magnitude of this variable is larger than the magnitude of the political control index, ranging from -.024 to -.027. Other variables largely retain the signs and significances they had in previous regressions. When lags are extended to five years, these patterns remain; as seen previously, lagged income growth becomes significant at the 10% level. As a test, the Republican control variables are used in the regressions; their signs are opposite to those of the Democratic variables.

The regressions are also repeated with the Theil index in place of the Gini coefficient. Political control has no effect on this variable. The college graduation variable has a large and highly significant positive impact on the Theil index, as does lagged income growth. Welfare retains the same sign and significance it possessed in regressions with the Gini coefficient. Little changes when the lags are extended to five years.

When individual variables are used in place of the control index, the Democratic governorship dummy shows a negative effect (-.0123) that is significant at the 10% level, but this is only significant if initial income is included. Interestingly, the percentage of Democrats in the lower house shows a positive and marginally significant (at the 10% level) effect on the Theil index -- the individual variables show the same sign pattern as they did when the Gini coefficient was the dependent variable. Once again, there is little variation between the one and five year regressions, though the Democratic governorship dummy is no longer significant over five year periods. When the Atkinson index is the dependent variable, the results appear similar in signs and significances; however, the Democratic governorship dummy variable is never significant.

If the top 1% income share is used as the dependent variable and the control index is included as a regressor, regardless of the lag length examined, the signs and significances of the political control variable are similar to their counterparts in regressions with the Theil index. However, when individual political variables are used, the percentage of Democrats in the upper house has a negative impact significant at the 5% level, over both one and five year periods. The magnitude of the negative impact exerted by the percentage of Democrats in the upper house is significantly larger than many of the magnitudes observed so far, around -.022. It decreases greatly over five year periods.

The index of political control has a robustly significant and positive effect on the Gini coefficient. However, it has an insignificant impact on the Theil and Atkinson indices and the top 1% income share (under one specification, the index has

a marginally significant impact, but it does not hold up over time periods or the exclusion of initial income). Despite being significant at the 5% or 1% level, the political control index has a small effect -- its magnitude ranges from .00144 to .00168 (if the index went from its minimum value of -2.5 to its maximum value of 2.5, the Gini would increase by between .0072 and .0084).

When other measures of political control -- three different variables that reflect the percentage of Democrats in the upper house, the percentage of Democrats in the lower house, and a dummy variable that is 1 if there is a Democratic governor in the state -- are used in place of the political control index, these variables are consistently significant for some measures of inequality. The percentage of Democrats in the upper house has a negative and significant effect on the Gini and the top 1% income share over one and five year periods, with a magnitude 100 times larger than the effect of the control index. The percentage of Democrats in the lower house generally shows a significant (at the 10% level only) and positive effect on all measures of inequality except for the Gini. This effect seems especially strong for the Theil index -- the magnitude of the coefficient is around .1 for one year periods. This means that a larger number of Democrats in the lower house of state legislatures may lead to an increase in inequality, which would indicate that Bartel's national trends are not necessarily applicable at the state level. These regressions are summarized below in Tables 26 - 31. Coefficients are multiplied by 100 for easier reporting.

Table 26 - Annualized Impact (x100) of the Political Control Index on Several Measures of Inequality

Lag	Gini	Theil	Atkinson	Top 1%
1 Year	0.14**	0.33	0.06	0.06
5 Years	0.17***	0.12	0.06	0.08

Robust standard errors
 *** p<0.01, ** p<0.05, * p<0.1

Table 27 - Annualized Impact (x100) of the Political Control Index on Several Measures of Inequality (Lagged Growth Included in Regression Analysis)

Lag	Gini	Theil	Atkinson	Top 1%
1 Year	0.15**	0.43	0.08	0.07
5 Years	0.17***	0.29	0.08	0.11*

Robust standard errors
 *** p<0.01, ** p<0.05, * p<0.1

Table 28 - Annualized Impact (x100) of the Other Measures of Political Control on Several Measures of Inequality Over 1 Year Periods

	Gini	Theil	Atkinson	Top 1%
Democratic Governor	-0.19	-1.02	-0.18	-0.04
% Dems in Upper House	-2.73**	-4.38	-1.03	-2.22**
% Dems in Lower House	1.10	10.90*	2.08*	1.92*

Robust standard errors
 *** p<0.01, ** p<0.05, * p<0.1

Table 29 - Annualized Impact (x100) of the Other Measures of Political Control on Several Measures of Inequality (Lagged Growth Included in Regression Analysis) Over 1 Year Periods

	Gini	Theil	Atkinson	Top 1%
Democratic Governor	-0.21	-1.23*	-0.22	-0.07
% Dems in Upper House	-2.42**	-3.90	-0.90	-2.23*
% Dems in Lower House	0.75	10.40*	1.97*	1.82

Robust standard errors
 *** p<0.01, ** p<0.05, * p<0.1

Table 30 - Annualized Impact (x100) of the Other Measures of Political Control on Several Measures of Inequality Over 5 Year Periods

	Gini	Theil	Atkinson	Top 1%
Democratic Governor	-0.03	-0.08	-0.02	0.00
% Dems in Upper House	-0.69***	-1.96	-0.38*	-0.72**
% Dems in Lower House	0.09	2.44*	0.42*	0.42*

Robust standard errors
 *** p<0.01, ** p<0.05, * p<0.1

Table 31 - Annualized Impact (x100) of the Other Measures of Political Control on Several Measures of Inequality (Lagged Growth Included in Regression Analysis) Over 5 Year Periods

	Gini (Lagged Growth Included)	Theil (Lagged Growth Included)	Atkinson (Lagged Growth Included)	Top 1% (Lagged Growth Included)
Democratic Governor	-0.03	-0.15	-0.01	-0.01
% Dems in Upper House	-0.67***	-1.77	-0.35	-0.70**
% Dems in Lower House	0.08	1.97	0.35*	0.34*

Robust standard errors
 *** p<0.01, ** p<0.05, * p<0.1

Total Effect of Political Control on Growth

Using the equations that involved the political control index, I calculate the total effect of the index on growth, which includes the direct effect of political control on growth and the indirect effect on growth through the Gini coefficient. The indirect effect is obtained by multiplying the observed effect of political control on the Gini and the observed effect of the Gini on growth. The direct effect of political control on growth is taken from the same estimation that contained the Gini and political control as regressors and the growth rate as the dependent variable. These effects (calculated both for linear models and non-linear models that relate inequality to growth) are summarized as ranges in Tables 32 and 33 below. While the effect of political control is still reported multiplied by 100, the correct level is used in calculations.

Table 32 -- Ranges (in %) of the Total Effects of Political Control Index on Growth in Linear Models

	Effect of Control Index on Gini (x100)	Effect of Gini on Growth	Indirect Effect on Growth Through Gini	Direct Effect of Control on Growth	Total Effect= Direct Effect + Indirect Effect
1 Year	0.140 to 0.150	-8.7 to -18.1	-0.013 to -0.027	-0.075 to -0.092	-0.088 to -0.114
5 Year	0.034 to 0.033	-5.5 to -10.5	-0.002 to -0.004	-0.032 to -0.043	-0.034 to -0.045

Table 33 - Ranges of the Total Effect of Political Control Index on Growth in Quartic Models

	Effect of Control Index on Gini	Effect of Gini on Growth	Indirect Effect on Growth Through Gini	Direct Effect of Control on Growth	Total Effect= Direct Effect + Indirect Effect
1 Year	0.144 -0.151	-11.0 - -16.0	-0.016 - -0.024	-0.11 - -0.15	-0.125 - -0.173
5 Year	0.032 - 0.034	-2.0 - 12.0	-0.00 - -0.04	-0.01 - -0.013	-0.012 - -0.015

When inequality is modeled to have a linear effect on growth, the total effect of political control on growth ranges from -.088% to -.114% over single year periods, and from -.034% to -.045% yearly over five year periods. If the political control of a state were to move from Democratic control (-2.5) to Republican control (2.5) this would result in a decrease in growth of up to .6% in a year. The mean growth rate over the time period examined is .06; thus a loss of more than a half percent of growth is not negligible. When inequality is modeled as impacting growth through a quartic function, the total impact of the political control index on growth ranges from -.125% to -.173% over single year periods, and from -.012% to -.015% over five year periods. These effects are larger than the linear effects; a swing from Republican

control to Democratic control would decrease growth by between -.7% and -.87% in a year.

Chapter 5: Discussion

Inequality and Growth

Inequality, when measured by the Gini coefficient, has a robustly significant impact on growth. When this impact is assumed to be linear, it is negative over time periods shorter than twenty years. Over twenty year intervals, the impact becomes positive.

A quartic relationship between inequality and growth is significant in a number of specifications. This quartic has a positive sign on its first degree term and alternating signs after. However, when it is evaluated at the mean value of the Gini coefficient in my data, it almost always has a negative impact on growth for time periods shorter than twenty years. The quartic findings suggest that to a certain point, inequality may create an additional incentive to work, or allow the wealthiest members of the population to invest in large productive projects that the poor cannot afford to invest in. Once inequality passes a certain level, the inability of the poor to obtain any loans or to invest in education, the lack of high return investments from the poor, and the decreasing incentive to work due to the seemingly impassable gap between the rich and the poor may lead inequality to negatively impact growth.

At any level of inequality near the mean levels in US states from 1969 to 2005, it seems that inequality has a negative impact on growth in periods shorter than twenty years. In both linear and non-linear specifications, the short run impact of inequality is large: the mean annual growth rate is around 6%, and the negative impact of the Gini coefficient is often larger than this.

The declining size of the negative magnitude of the Gini coefficient over time, and the switch in the sign on the Gini coefficient over twenty year periods may reflect measurement error (it is likely that causation over longer periods is less reliable than causation over the 1 and 5 year periods), but it may also be the result of factors not included in the analysis. One such factor is mobility, which may be limited in the short term but more important in the long term. A second factor may be unmodeled responses to the reduced short-term growth; to the extent such responses are successful in counteracting short term declines in growth, it may appear that inequality is responsible for the long-term reversal.

Because most of the benefit of growth over the last 30 years has accrued to the upper 1% of income earners, I examine this portion of the distribution in the regressions. The top 1% income share is often significant -- though it is not always robust to different statistical techniques, and it switches signs over time. The inclusion of the top 1% income share in regression analysis often leads to an increase in the magnitude of the impact of the Gini coefficient -- when the very top end of the income distribution is accounted for, an increase in the overall spread of the income distribution has a larger negative impact on growth. The top 1% share is significant when included in several quartic specifications; however, there is no pattern relating the impact of the Gini and the inclusion of the top 1% income share.

When the top 1% share of income increases, it is likely that the value of the Gini will increase as well, unless the income share of the bottom 1% is simultaneously increased to prevent the widening of the income distribution. All else equal, however, the size of the increase in the top 1% income share will outweigh the

size of the increase in the Gini coefficient -- a 1% increase in the top 1% income share will not increase the Gini by 1%, since the correlation between these two variables is less than 1. When related to growth by a linear function, the negative size of the coefficient on the Gini is often smaller than the size of the coefficient on the top 1% income share, but when related to growth by a quartic function, the size of the Gini's negative impact evaluated at the mean is often larger than the impact of the top 1% income share. Generally, regardless of whether the relationship between the Gini and income growth is modeled as linear or non-linear, the impacts of the top 1% share and the Gini coefficient work in opposition over shorter time periods. While the top 1% share is related to growth, it is not driving the relationship between inequality and growth.

The use of other measures of inequality in place of the Gini did not result in robustly significant linear or non-linear relationships between inequality and growth for the time period I examined. The middle class quintile share is rarely significant, and is not used in non-linear specifications, but its impact on growth dwarfs the impact of the Gini when significant. This is another interesting (though not robust) result -- corroborated elsewhere -- obtained from the use of multiple inequality measures in the same specification. It appears that for examination of the inequality-growth relationship, the Gini is the only measure of inequality which has a consistently significant impact on growth.

Political Variables

Overall, political control at the state level has a statistically significant impact on inequality and growth. The direction of this effect mirrors the effect seen by

Bartels (2008) at the national level, but the magnitude of the effect is smaller. The total effect of politics on growth -- the combination of its indirect effect on inequality and its direct effect on growth -- is between .088% and .173% annually, so a shift in the political climate of a state from Republican to Democrat leads to an increase in the annual growth rate between .44% and .87%.

In the short run, the policies pursued by Democrats -- even though differences in Democrats regionally and over time are ignored -- directly benefit growth, and decrease inequality, which also indirectly increases growth. The policies pursued by Republicans have the opposite effects. This result, however, does not account for differences in party policies over time and in different regions, and it is possible that certain a party's policies at various times in specific regions may have more impact than the same party's policies at other times or in other regions. At the national level, Democrats often attempt to improve employment, growth, and social services, following expansionary policies with short run benefits, while Republicans focus on reducing inflation and cutting spending (Bartels 2008). If these policies are mirrored at the state level, they may be responsible for the observed impact of the political variables.

The effect of politics was not examined over periods longer than five years. It is possible that in states where the political climate is fairly stable, the relationship may change in the long run. However, in states where the political climate is volatile, it seems likely that Republicans pursuing policies that increase inequality -- sharply decreasing short run growth -- would be punished at the polls, leading to a leftward shift in political control, reducing inequality, and increasing growth.

Interestingly, when the overall political index is decomposed and single variables representing a party's control over various portions of the political apparatus are used, some of these variables are statistically significant with magnitudes much larger than the magnitude of the index. The governorship variable is rarely important, but the percentage of Democrats in the upper house of the state legislature sometimes has a significant negative effect on inequality (but not growth). The percentage of Democrats in the lower house is often significant (though usually at the 10% level) with a positive effect on both growth and inequality. The statistical importance of the lower house of the legislature -- and the lack of importance of the governorship dummy, especially in comparison with Bartels' findings on the importance of presidents -- is unexpected.

There are a number of possible explanations for the observed magnitude of the effects of politics on growth and inequality at the state level. It is possible that national politics, as well as factors I control for in my analysis, such as education and the industrial mix within a state, outweigh the impact of state politics. The impact of politics at the state level may also operate through included factors such as education, welfare spending, and industrial development. Also, as noted before, I do not take into account the political differences between Democrats and Republicans in different regions, or the differences over time -- the political climate in the country has changed significantly since 1969. Despite these shortcomings, the political control index shows a statistically significant impact on inequality and growth, and a noticeable total short run effect on growth.

Panel and Econometric Issues

The yearly panel employed in this thesis has a number of advantages. The quality of US data greatly reduces measurement error; the large number of observations increases the possible statistical techniques available and the accuracy of the estimates, while also reducing the extent of multicollinearity; the similarity of institutions across-states makes coefficients more stable and less subject to the impact of outliers; the richness of data available in the US reduces the potential for omitted variable bias; and the interconnectedness of states means that any relationship observed between inequality and growth may be substantial, as suggested by Partridge (1997, 2004). Another advantage of the yearly panel is the ability to examine in depth the changes in the relationship between inequality and growth over time. In the cross-country literature, Forbes (2000) compares 5 and 10 year periods and finds the impact lessening, but there is often little lag comparison. Partridge (1997) and Panizza (2002) compare ten year and thirty year periods; Frank (2009) focuses on the long term. In this thesis, I am able to examine changes over time from one to twenty year periods.

Cross-country regressions are notoriously plagued by econometric difficulties, and cross-state regressions suffer from some of the same problems. Of all the estimators used in this thesis, the most accurate is likely fixed effects estimation with both state and year effects. The inclusion of state fixed effects removes any constant state factors that may be causing omitted variable bias, and the addition of yearly fixed effects removes any single year shocks that might persist and create autocorrelation. The standard errors are adjusted for observed heteroskedasticity, and

the control variables are lagged to remove endogeneity in the system. Ordinary least squares is the second most reliable estimator, since, as Wooldridge suggests, I adjust its standard errors to account for heteroskedasticity and serial correlation. FGLS and fixed effects with state effects and errors adjusted for serial correlation only take into account first degree autocorrelation, and thus are not reliable if autocorrelation extends beyond that. Post-estimation tests indicate that Arellano - Bond is not a suitable form of estimation for this type of data.

There is evidence of multicollinearity in the regressions; the variables that consistently had VIF values above ten -- initial income, the top 1% income share, and welfare spending -- were removed from some estimations (models 1 and 3 do not contain these variables) in an attempt to test the robustness of the observed relationship. Regressions remain unbiased when multicollinearity is present, although it is likely that standard errors will increase in the estimation process. Standard errors will increase more when fixed effects techniques are used, due to the use of less available variation in the estimation process.

There is also evidence of functional form misspecification across a wide variety of control variables, measures of inequality, and linear and non-linear functions. A number of variations of the specifications used in previous work failed the Ramsey specification test. While I found strong evidence of a non-linear relationship between the Gini coefficient and economic growth, it is possible that more than one variable has a non-linear relationship, or that some factor that is important in this relationship has been omitted.

Comparing Results with Previous Studies

No earlier work incorporates political variables at the state level or examines non-linear relationships in detail with United States data. In addition, many studies do not have yearly observations and often fail to use a wide variety of statistical techniques.

Inequality and Growth

Partridge (1997) uses OLS and finds a positive relationship between growth and inequality. Partridge's effects were generally opposite in sign and larger in magnitude than those in this study; for the longer period (Partridge used a thirty year period, and I used a twenty year period), the signs were the same (positive). He obtains a yearly effect ranging from 6.27% to 12.4% over ten year periods and a yearly effect around 7.55% over thirty year periods. Over ten year periods, I obtained impacts ranging from 0% to -2.4% using OLS; I did not examine thirty year periods, but the yearly effects I observed over twenty year periods showed a generally declining trend. When Partridge includes the middle quintile share in his analysis, the yearly Gini effect ranges from 18.2% to 21.7%, and the middle quintile income share yearly effect ranges from 73.1% to 81.6%. In contrast to Partridge's findings, I rarely find a robust and significant impact of the middle quintile income share; however, when it is significant, it does have a large magnitude relative to the magnitude of the Gini coefficient, roughly 40%. While the middle class income share appears to have a large impact on the growth rate when significant, the size of this coefficient seems too large to be plausible.

Partridge (2004) performed a second OLS analysis and again found that the Gini has a positive effect on growth, but the effect is smaller than in his earlier study, ranging from 4.78% to 5.4% yearly over thirty year periods and from 2.51% to 4.12% yearly over forty year periods. Once again, these results are opposite in sign to those I obtained, although the magnitude (absolute value) appears closer to the magnitude of the effect in this study. (The time periods are longer than the ones I examine; these effects are likely to be larger than mine would be if the pattern I observe in coefficient magnitudes -- decreasing impacts on growth as the lag length of the control variables increases -- were to continue.) Partridge (2004) also uses fixed effects; his fixed effects estimates result in a yearly impact of the Gini ranging from -2.39% to 3.31% over forty years. When I use fixed effects estimation over twenty year periods, the impact of the Gini ranges from 1.9% to 4.5% yearly. Partridge's results are consistently larger than mine in magnitude; they also fluctuate in direction while mine are consistently positive over the 20 year period.

Panizza (2002) finds that inequality has a negative effect on growth in periods up to twenty years. The magnitude of the impact in his study is smaller than the effect observed in my analysis (though he uses different data and looks at the time period from 1940 - 1980). Using OLS, he finds the Gini to have an impact of -.39% yearly over ten years -- in comparison to 0% to -2.4% in this thesis -- and he finds no significant effect over twenty years -- while I find a significant negative effect of 1.3% to 4.7%. Using fixed effects, Panizza finds the Gini to have an effect between -.6% and -.78% yearly; this changes to a positive effect (ranging in magnitude from .51% to .61%) over twenty year periods. The switch of the sign on the Gini

coefficient observed by Panizza when using fixed effects between ten and twenty year periods also occurs in my own work. Panizza also finds evidence of a quartic function relating inequality to growth, and his quartic relationship also indicates that the Gini coefficient has a negative impact on growth for any values near the mean in his data.

Frank (2009) conducts the only previous study of inequality and growth at the state level which employs the Theil and Atkinson indices as well as the top 1% income shares in empirical analysis. In general, his effects are much smaller than those I found, and they often have different signs. He finds that a two standard deviation increase in the top decile share, top 1% share, Gini coefficient, Theil index, or Atkinson index leads to a yearly increase in the long run growth rate of .072% (- .23% - -.45% in my fixed effects regressions using twenty year lags), .066% (insignificant in my work), .008% (.198% to .468% in my work), .081% (-.477% to -.80%), and .023 - .063% (-.274% to -.524%) respectively. Frank's analysis extends from 1945 -- 2004, a period during which inequality fell and then rose, while my panel extends from 1969 -- 2005, a period during which inequality steadily increased. In addition, Frank uses one set of explanatory variables (human capital and industrial wage variables, instead of the industrial employment percentages used in this thesis), focuses on the long run growth rate (it is unclear how many years are used in Frank's study), and does not examine non-linearities.

In the cross-country literature, Barro (2000) and Banerjee and Duflo (2003) do not find their results robust to different sets of control variables or functional specifications, but Alesina and Rodrik (1994) and Forbes (2000) obtain results that

remain robust to a variety of tests. Alesina and Rodrik examine the relationship between inequality and growth over fifteen and twenty-five year periods, using OLS and two stage least squares estimation. Over fifteen years, they find inequality to have a yearly impact on growth ranging from $-.381\%$ to $-.647\%$; when they examine twenty-five year periods, they find inequality's impact to be comparable, between $-.228\%$ and $-.639\%$. Using OLS and lagging the Gini coefficient twenty years, I found inequality to have a larger negative impact, ranging from -1.3% to -4.7% .

Forbes uses panel estimators -- fixed effects, random effects, and Arellano - Bond estimators -- and examines shorter timer periods, from five to ten years in length. She finds inequality to have a yearly impact of $.026\%$ to $.072\%$ over five years, and a yearly impact of around $.013\%$ over ten years. Using fixed effects, I find a negative effect over five year periods, and a generally inconsistent effect over ten year periods. However, using Arellano - Bond estimators, I find inequality has a positive impact on growth over both time periods, though the effect I observe is much larger than the effect seen in Forbes -- never falling below 1% yearly.

Voitchovsky (2005) is one of the few economists to use a measure of the top end of the income distribution in conjunction with the Gini coefficient in her analysis. She finds these two variables to be jointly significant -- though often not individually significant. The Gini coefficient, moreover, has a consistently negative impact, and the top end measure (she uses the 90/75 percentile ratio) has a consistently positive impact. I find similar results using the Gini and the top 1% income share, though both my measures are often significant individually. Voitchovsky relies largely on

Arellano and Bond estimators, and has a small panel data set with observations every five years.

Overall, my results are most similar to those of Panizza at the state level and Alesina and Rodrik in cross-country work, and differ both in sign and magnitude from the results obtained by Partridge, Frank, and Forbes. This may be the result of a variety of factors, including the use of different control variables and data from different time periods. Previous work with two measures of inequality, one measure reflecting the whole income distribution and a second the top end of the distribution, yields results similar to those of my study. While Banerjee and Duflo (2003) suggest that it is an important aspect of the relationship, earlier papers do not generally address non-linear specifications, which I find to be robust and significant. The presence of a non-linear relationship between inequality and growth, at least in the United States, may be partially responsible for the inconsistent results obtained in the previous literature. This is an important finding that needs to be investigated further.

Political Ideology

In a cross-country study, Bjornskov (2008) finds that a move from a center government to a center-left government would decrease growth by .28%; a move to a moderately rightwing government leads to an increase in growth by a comparable amount. Bjornskov's result is opposite in sign (but comparable in magnitude) to my findings.

Bartels (2008) examines the difference in growth rates in the United States under Democratic and Republican presidents, controlling for a number of other factors that might effect economic growth. He finds that for the bottom four quintiles

of income earners, growth is 1.23% to 2.32% higher under Democratic presidents, and that these results are significant at the 5% level. Growth is also .5% higher for the top 5% of income earners, but this result is not statistically significant. While I examined the entire income distribution rather than specific portions, I obtain results that were similar but smaller in magnitude. One might expect national politics to have a greater effect on growth than state politics.

Future Research

Since inequality measures exist at least as far back as 1945, I hope to extend the rest of my panel back to this date, allowing for a more comprehensive look at the relationship between inequality and growth and how it changes over time. Additional work is needed to examine the relationship between other measures of inequality and the Gini in order to determine how these different measures -- especially the Gini, Atkinson, and Theil -- affect growth. Additional research should also address the models used in previous research that failed specification tests. Further investigation of the nature of the non-linear relationship between inequality and growth, the use of multiple measures of inequality (that capture different areas of the income distribution), and experimentation with the proper set of control variables, may also be fruitful.

Ideally, one would be able to estimate two equations, both containing a measure of political control or partisanship -- one with growth as the dependent variable and one with inequality as the dependent variable -- simultaneously. However, in order to identify this system, an instrument is required that impacts politics but not growth, or vice versa. The creation of a more refined measure of

political partisanship at the state level -- which in some way accounts for the different positions of Democrats and Republicans in different states and over time -- would also be very useful for a more thorough exploration of the importance of state politics in creating growth and inequality. It is also important to determine the channels through which political power at the state level impacts the economy; these channels may be different from those at the national level.

Conclusion

Inequality, politics, and growth appear to be linked, and these links seem to be especially strong in the short run -- over one and five year periods. Inequality, as measured by the Gini coefficient, has a significant and negative impact on growth that is fairly robust to changes in control variables and estimation techniques. The top 1% income share and a quartic function of the Gini coefficient are generally significant, indicating inequality is related to growth in a non-linear fashion. Over the longest time period examined (twenty years), the Gini coefficient has a positive effect on growth, which may perhaps be due to regional mobility or other non-modeled factors. Other measures of inequality do not display the same relationships with growth as the Gini coefficient.

A measure of state political control has significant effects on both growth and inequality. As seen at the national level, the total effect of this variable on growth indicates that Democratic control leads to increased growth and decreased inequality (indirectly increasing growth), while Republican control has the opposite effects. While this thesis represents only a first step towards including US political variables in an examination of the relationship between inequality and growth, it appears that such variables are important at the state level. Ultimately, research aimed at identifying variables that simultaneously enhance growth and reduce inequality may provide a significant contribution to policy.

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