We investigate the causal relationship between income inequality and economic freedom using data from U.S. states over the period 1981 to 2004 within a panel error correction model framework. The results indicate bidirectional causality between income inequality and economic freedom in both the short and the long run. These results suggest that high income inequality may cause states to implement redistributive policies causing economic freedom to decline. As economic freedom declines, income inequality rises even more. In other words, it is quite possible for a state to get caught in a vicious circle of high income inequality and heavy redistribution. (JEL D63, H11)

I. INTRODUCTION

Over the last three decades, inequality in the United States grew significantly. The Gini index of income inequality was below 0.40 in 1980. Today, it is close to 0.45. Between 1980 and 2009, while the real income of the population in the bottom fifth grew slightly more than 10% and the middle fifth by 15%, the income of the top 5% grew more than 45%. Today, the income share of the bottom fifth is less than 5% while the highest fifth is more than 50%. As Page and Jacobs (2009) argue, growing income inequality in the United States is recognized as a problem from across the political spectrum—from liberal democrats like Barack Obama to conservative republicans like George W. Bush. Although not everyone agrees that inequality is actually a problem, almost three-fourths of Americans agree that differences in income are too large (Page and Jacobs 2009, 40). Nevertheless, government policies to reduce inequality are still quite controversial. Page and Jacobs define Americans as conservative egalitarians. Is conservative egalitarianism an oxymoron? Is it possible to achieve equality while promoting policies toward economic freedom? In this paper, we analyze these questions using data from U.S. states covering almost a quarter of a century.

The effects of economic freedom on income inequality are threefold. First, it creates opportunities for the poor by creating equal access to property rights necessary for the generation of capital for everyone. Second, economic freedom promotes economic growth which in turn affects income distribution. Kuznets (1955, 1963) hypothesizes that income distribution in an economy worsens in the early stages of the economic development, but then it improves as it reaches later stages of development. According to Kuznets, this is because of a shift of labor from low- to high-productivity sectors in the initial stages of development, which results in a widening gap in incomes. As the economy develops, however, the high-productivity sector dominates the economy, and income inequality decreases. In other words, there is an inverse-U-shaped relationship between income inequality and economic growth. Several studies investigating the relationship between income inequality and economic growth in the United States do not find empirical evidence supporting Kuznets’ hypothesis. They do, however, find a U-shape relationship between the two variables revealing an indirect relationship between economic freedom and income inequality. Finally, economic freedom limits
redistribution from the rich to the poor. A regressive tax system is generally assumed to raise income inequality, whereas a progressive tax system is assumed to reduce it. Dincer and Gunalp (2012) find a negative relationship between the marginal tax rates and income inequality in the United States.

There are several empirical studies analyzing the relationship between economic freedom and income inequality. Not surprisingly, their findings have yielded mixed results. The lack of consensus is partly due to the differences in the samples and the empirical methodology. Our study advances the literature on several fronts. First, unlike previous studies which rely on cross-sectional data, we exploit both time series and cross-sectional variation in the data. Second, and perhaps most importantly, we analyze the Granger-causal relationship between economic freedom and inequality within a panel error correction model framework. Previous studies assume a unidirectional causal relationship from economic freedom to inequality. In democratic countries, such as the United States, high income inequality forces governments to follow policies that redistribute income from the rich to the poor. Given that redistributive policies cause economic freedom to decline, unidirectional causality is rather a strong assumption.

Our results reveal bidirectional Granger-causality in both the short and long run between economic freedom and inequality. Section II provides a brief overview of the empirical literature analyzing the relationship between economic freedom and income inequality. Section III describes the data while Section IV discusses the methodology and empirical results. Concluding remarks are given in Section V.

II. LITERATURE REVIEW

Although there is an extensive literature analyzing the relationship between economic freedom and the growth rate of income, there are only a few studies related to the impact of economic freedom on the distribution of income. While Berggren (1999) finds a positive relationship between the level of economic freedom and income inequality, Scully (2002) finds that higher levels of economic freedom are associated with lower levels of income inequality. Both studies use the Fraser Institute Economic Freedom index to measure economic freedom across countries.

In addition to the relationship between the levels, Berggren (1999) also investigates how changes in economic freedom affect income inequality. He finds a negative relationship between the change in economic freedom and income inequality. He argues further that implementing policies favoring economic freedom may increase income inequality in the short run due to the redistribution benefiting the rich, but in the long run economic freedom may benefit the poor due to economic growth. On the other hand, Carter (2006) asserts that Berggren errs in the interpretation of his results. According to Carter (2006, 164), Berggren’s results indicate that the short-run effect may be toward more equality, but estimated long-run effect of economic freedom is toward more inequality. Without more information it is not possible to determine whether the estimated effects are statistically significant.

Both Berggren (1999) and Scully (2002) use a small sample of countries, whereas Carter (2006) estimates a linear fixed effects model using an unbalanced panel of 123 countries over six time periods between 1975 and 2004. In contrast to Berggren and Scully, Carter finds a positive relationship between economic freedom and income inequality, particularly at higher levels of economic freedom.

The Fraser Institute not only produces the economic freedom index across countries, but also for U.S. states. Ashby and Sobel (2008) use data from a pooled sample of U.S. states and find that changes in economic freedom are associated with higher income and higher rates of income growth for all income groups (lowest quintile, middle quintile, and highest quintile) and with lower relative income inequality, which supports Berggren’s (1999) results. Nevertheless, Ashby and Sobel do not find evidence supporting Berggren’s result that the level

5. For the world index see Gwartney, Lawson, and Hall (2010), for the U.S index see Ashby et al. (2010).
of economic freedom is negatively related to income inequality.

Unfortunately, none of these studies address the dynamic nature of the problem in their analyses. Specifically, these studies do not address the issue of Granger-causality between economic freedom and income inequality instead relying on the implicit assumption that the direction of causality runs from economic freedom to inequality.\(^6\) Our study will address these shortcomings in the literature.

III. DATA

We use annual data from U.S. states from 1981 to 2004.\(^7\) Using within-country data in an empirical study offers several advantages. The likelihood of problems arising due to data incomparability is minimal. Data on economic freedom and income inequality for U.S. states are more comparable than those for different countries. More importantly, it is possible to hold political institutions more or less constant. We measure income inequality (GINI) using the Gini index based on data from the U.S. Census Bureau compiled from the U.S. Current Population Survey (CPS) data on pretax household incomes. Following the previous literature the Fraser Institute Economic Freedom index (EF) to measure economic freedom across states is utilized. The Fraser Institute Economic Freedom index captures the variation in economic freedom across U.S. states in three important areas: government spending, taxation, and labor market freedom. The index runs from 0 to 10 with a 10 being the highest possible score denoting the highest level of economic freedom. There is, in fact, a relatively large variation in economic freedom across the U.S. states. On the basis of these averages across the two and a half decades covered in our data, West Virginia has the lowest level of economic freedom, whereas Delaware has the highest. In both states, economic freedom is at least two standard deviations lower or higher than the U.S. average.

In addition to the inequality and economic freedom variables, we include a set of state economic and demographic control variables to minimize potential omitted variable bias (Lütkepohl 1982). We control for real per capita income (Y) with data obtained from the U.S. Bureau of Economic Analysis. The two demographic variables included are education (EDUC) measured as the share of elementary and secondary school enrollment in the population of 5- to 17-year-old persons obtained from the National Center for Education Statistics and the total population (POP) from the Census Bureau for each state. The summary statistics associated with each variable are presented in Table 1.

IV. EMPIRICAL METHODOLOGY AND RESULTS

The panel error correction model framework is employed to capture the Granger-causal dynamics between income inequality and economic freedom. However, before the panel error correction model can be estimated the time series properties of the respective variables need to be examined. The analysis begins by investigating the order of integration of the respective variables using a battery of unit root and stationarity tests.\(^8\) Levin, Lin, and Chu (2002) set forth a panel-based augmented Dickey-Fuller (ADF) unit root test that assumes homogeneity in the dynamics of the

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>GINI</td>
<td>0.43</td>
<td>0.03</td>
<td>0.35</td>
<td>0.52</td>
</tr>
<tr>
<td>EF</td>
<td>6.53</td>
<td>0.60</td>
<td>4.7</td>
<td>8.4</td>
</tr>
<tr>
<td>Y</td>
<td>14,446</td>
<td>2,600</td>
<td>8,536</td>
<td>24,259</td>
</tr>
<tr>
<td>EDUC</td>
<td>0.90</td>
<td>0.04</td>
<td>0.79</td>
<td>1</td>
</tr>
<tr>
<td>POP</td>
<td>5,149,830</td>
<td>5,603,053</td>
<td>418,491</td>
<td>35,600,000</td>
</tr>
</tbody>
</table>

Notes: Variable definitions and sources: GINI = Gini index of income inequality, Census Bureau; EF = Economic freedom index, Fraser Institute; Y = Real personal income per capita (Baseperiod: 1982–1984 = 100), Bureau of Economic Analysis; EDUC = Share of elementary and secondary school enrollment in the population between 5 and 17 years old education, National Center for Education Statistics; POP = Population, Census Bureau.

---

6. Granger-causality is a statistical test for determining whether one time series is relevant in forecasting another time series. For example, the time series X Granger-causes time series Y if lagged values of X (alongside lagged values of Y) provide statistically significant information about the future value of Y (Granger 1969). However, Granger-causality tests have several caveats. In particular, Granger-causality tests are sensitive to lag length selection and potential omitted variables. In an attempt to address these concerns, we employ likelihood ratio tests for the determination of lag length and case our analysis in a multivariate framework to mitigate the potential omitted variable bias.

7. Although the economic freedom index is available until 2007, our sample covers the time period until 2004 due to the unavailability of the data for some of the control variables.

8. Details of the panel unit root and stationarity tests are omitted for the sake of brevity but available upon request from the authors.
autoregressive coefficients for all panel units. On the other hand, the Im, Pesaran, and Shin (2003) panel unit root test allows for heterogeneity in the dynamics of the autoregressive coefficients for all panel units. Contrary to Levin, Lin, and Chu and Im, Pesaran, and Shin, Maddala and Wu (1999) suggest the use of nonparametric panel unit root tests, which combine the $p$ values from individual unit root tests, in the estimation of Fisher-ADF and Fisher-PP tests. Finally, the Carrion-i-Silvestre, del Barrio-Castro, and Lopez-Bazo (2005) test, which is a generalization of the Hadri (2000) panel stationarity test based on the assumption that the long-run variance is either homogeneous or heterogeneous, is also examined. Under the Levin, Lin, and Chu; Im, Pesaran, and Shin; Fisher-ADF; and Fisher-PP tests the null hypothesis is a unit root while the alternative hypothesis is the absence of a unit root. On the other hand, the Carrion-i-Silvestre, del Barrio-Castro, and Lopez-Bazo’s test assumes stationarity under the null hypothesis. Table 2 reports the panel unit root and stationarity tests which reveal that each variable is integrated of order one.

Given each variable in the panel is integrated of order one, the Larsson, Lyhagen, and Löthgren (2001) panel cointegration procedure is utilized to determine the long-run relationship among the variables in question. Similar to the Johansen’s (1988, 1995) cointegration methodology, the Larsson, Lyhagen, and Löthgren’s procedure utilizes a likelihood-based framework for the testing and estimation of cointegrated panels within a panel vector error correction model. The Larsson, Lyhagen, and Löthgren’s procedure offers several advantages over residual-based cointegration tests. First, unlike Pedroni’s (1999, 2004) approach which assumes there is only one cointegrating vector, the Larsson, Lyhagen, and Löthgren approach allows for more than one cointegrating vector. Second, with the Larsson, Lyhagen, and Löthgren procedure, no choice has to be made regarding the normalization of variables. Third, though the cointegrating relations are restricted to each cross section under the Larsson, Lyhagen, and Löthgren procedure, the rest of the model is unrestricted allowing for a substantial amount of short-run dependence between the groups.

The Larsson, Lyhagen, and Löthgren (2001) panel cointegration procedure is described as follows. The panel data set consists of $N$ cross section (50 states) observed over $T$ time periods (24 years). Let $i = 1, \ldots, N$ represent the 50 states, $t = 1, \ldots, T$ the sample time period 1980 to 2004, and $j = 1, \ldots, p$ the variables in each group. Thus, $y_{ijt}$ represents the $i$th group and the $j$th variable at time $t$. The data generating process for each of the groups can be characterized by the following heterogeneous VAR($k_i$) model:

$$Y_{it} = \sum_{k=1}^{k_i} \Pi_{ik} Y_{i,t-k} + \varepsilon_{it}, \quad i = 1, \ldots, N \tag{1}$$

where for each group $i$ the values $Y_{i,-k_i+1}, \ldots, Y_{i,0}$ are fixed and the errors $\varepsilon_{it}$ are independently identically distributed $N_p(0, \Omega_i)$. The heterogeneous error correction model is given as follows:

$$\Delta Y_{it} = \Pi_i Y_{i,t-1} + \sum_{k=1}^{k_i-1} \Gamma_{ik} \Delta Y_{i,t-k} + \varepsilon_{it}, \quad i = 1, \ldots, N \tag{2}$$

where $\Pi_i$ is of the order $p \times p$. If $\Pi_i$ is of reduced rank, it is possible for $\Pi_i = \alpha_i \beta_i'$, where $\alpha_i$ and $\beta_i$ are $p \times r_i$ and of full column rank. The reduced-rank estimation procedure allows for the estimation of $\Pi_i$ and hypothesis testing on the cointegrating rank as well as determination of the long-run coefficients, $\beta_i$, and the adjustment parameters, $\alpha_i$. If cointegration is determined using the trace statistic, the Larsson, Lyhagen, and Löthgren (2001) procedure permits one to test whether the cointegrating vector is homogeneous across states. In addition, the Larsson, Lyhagen, and Löthgren (2001) procedure allows for a robust test of cointegration that can be performed with cross-sectional dependence in the error terms of the panel without arbitrary normalization assumptions.

As shown in Panel A of Table 3, the null hypothesis of no cointegration is rejected in favor of panel cointegration with one cointegrating vector. Also, the null of homogenous cointegrating vectors is rejected as the test statistic, 67.31, exceeds both the asymptotic and bootstrapped critical values. Therefore, the Larsson, Lyhagen, and Löthgren (2001) panel test for cointegration indicates a common rank, $r = 1$, between income inequality, economic freedom, income, education, and population for the panel.


10. The residual based cointegration test of Pedroni (1999, 2004) is sensitive to both the usage of time dummies to account for potential cross-sectional dependence and variable normalization.
of U.S. states. Panel B of Table 3 displays the long-run parameter estimates associated with the cointegrating vector based on the Larsson, Lyhagen, and Löhsgren procedure. All of the coefficients are statistically significant at 1% level. The estimated coefficient of economic freedom is negative indicating the possibility of reducing income inequality while promoting policies toward economic freedom. The coefficient estimates of the control variables are consistent with earlier studies. While the estimated coefficients of income and education are negative, that of population is positive (Ashby and Sobel 2008; DeGregorio and Lee 2002).

Given the establishment of a long-run relationship among the variables, a panel vector error correction model is estimated to test for Granger-causality among the variables in question. Defining the lagged residuals from the long-run cointegration equation given in Panel B of Table 3, the following dynamic error correction model is estimated:

\( \Delta GINI_{it} = \xi_{1j} + \sum_{k=1}^{q} \psi_{11ik} \Delta GINI_{it-k} + \sum_{k=1}^{q} \psi_{12ik} \Delta Y_{it-k} + \sum_{k=1}^{q} \psi_{13ik} \Delta EDUC_{it-k} + \sum_{k=1}^{q} \psi_{14ik} \Delta POP_{it-k} + \psi_{15ik} \Delta EF_{it-k} + \lambda_{1i} \varepsilon_{it-1} + u_{1it} \)  

\( \Delta EF_{it} = \xi_{2j} + \sum_{k=1}^{q} \psi_{21ik} \Delta GINI_{it-k} + \sum_{k=1}^{q} \psi_{22ik} \Delta Y_{it-k} + \sum_{k=1}^{q} \psi_{23ik} \Delta EDUC_{it-k} + \sum_{k=1}^{q} \psi_{24ik} \Delta POP_{it-k} + \psi_{25ik} \Delta EF_{it-k} + \lambda_{2i} \varepsilon_{it-1} + u_{2it} \)  

\( \Delta Y_{it} = \xi_{3j} + \sum_{k=1}^{q} \psi_{31ik} \Delta GINI_{it-k} + \sum_{k=1}^{q} \psi_{32ik} \Delta Y_{it-k} + \sum_{k=1}^{q} \psi_{33ik} \Delta EDUC_{it-k} + \sum_{k=1}^{q} \psi_{34ik} \Delta POP_{it-k} + \psi_{35ik} \Delta EF_{it-k} + \lambda_{3i} \varepsilon_{it-1} + u_{3it} \)  

\( \Delta EDUC_{it} = \xi_{4j} + \sum_{k=1}^{q} \psi_{41ik} \Delta GINI_{it-k} + \sum_{k=1}^{q} \psi_{42ik} \Delta Y_{it-k} + \sum_{k=1}^{q} \psi_{43ik} \Delta EDUC_{it-k} + \sum_{k=1}^{q} \psi_{44ik} \Delta POP_{it-k} + \psi_{45ik} \Delta EF_{it-k} + \lambda_{4i} \varepsilon_{it-1} + u_{4it} \)

11. The authors thank Chris Tsoumas for providing the software routine to implement the Larsson, Lyhagen, and Löhsgren (2001) panel cointegration test.

**Table 2**
Panel Unit Root and Stationarity Tests

<table>
<thead>
<tr>
<th>Variables</th>
<th>IPS</th>
<th>LLC</th>
<th>Fisher-ADF</th>
<th>Fisher-PP</th>
<th>CBL (HOM)</th>
<th>CBL (HET)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GINI</td>
<td>-6.73</td>
<td>-0.37</td>
<td>17.62</td>
<td>27.84</td>
<td>36.71</td>
<td>37.87</td>
</tr>
<tr>
<td>ΔGINI</td>
<td>-6.29</td>
<td>-5.48</td>
<td>85.47</td>
<td>119.47</td>
<td>1.14</td>
<td>1.46</td>
</tr>
<tr>
<td>EF</td>
<td>-1.29</td>
<td>-0.72</td>
<td>24.38</td>
<td>27.84</td>
<td>31.06</td>
<td>32.16</td>
</tr>
<tr>
<td>ΔEF</td>
<td>-5.98</td>
<td>-5.48</td>
<td>81.07</td>
<td>119.52</td>
<td>1.57</td>
<td>1.81</td>
</tr>
<tr>
<td>Y</td>
<td>-0.29</td>
<td>-0.58</td>
<td>17.37</td>
<td>20.15</td>
<td>36.73</td>
<td>27.69</td>
</tr>
<tr>
<td>ΔY</td>
<td>-6.52</td>
<td>-5.66</td>
<td>83.44</td>
<td>109.81</td>
<td>1.25</td>
<td>1.74</td>
</tr>
<tr>
<td>EDUC</td>
<td>-0.88</td>
<td>-0.67</td>
<td>20.26</td>
<td>21.25</td>
<td>25.61</td>
<td>26.48</td>
</tr>
<tr>
<td>ΔEDUC</td>
<td>-4.98</td>
<td>-5.11</td>
<td>69.24</td>
<td>75.12</td>
<td>1.34</td>
<td>1.51</td>
</tr>
<tr>
<td>POP</td>
<td>-1.54</td>
<td>-0.64</td>
<td>25.66</td>
<td>31.06</td>
<td>34.09</td>
<td>36.74</td>
</tr>
<tr>
<td>ΔPOP</td>
<td>-6.99</td>
<td>-5.46</td>
<td>86.62</td>
<td>126.84</td>
<td>0.84</td>
<td>1.13</td>
</tr>
</tbody>
</table>

*aCritical values at the 1% level: IPS -4.64, LLC -0.84, Fisher-ADF 56.09, Fisher-PP 61.15, CBL (HOM) 6.73, and CBL (HET) 6.11.
TABLE 3
Panel Cointegration Tests and Long-Run Estimates

<table>
<thead>
<tr>
<th>Null Hypothesis</th>
<th>LR Test</th>
<th>(Asymptotic)</th>
<th>(Bootstrapped)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Cointegration Tests</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cointegrating rank</td>
<td>255.06**</td>
<td>116.93</td>
<td>234.55</td>
</tr>
<tr>
<td>$H_0: r = 0$</td>
<td>94.55</td>
<td>109.08</td>
<td>186.52</td>
</tr>
<tr>
<td>Homogeneous cointegration vectors</td>
<td>67.31**</td>
<td>34.74</td>
<td>54.93</td>
</tr>
<tr>
<td>$H_0: b_1 = b_2 = \ldots = b_N$</td>
<td>67.68</td>
<td>67.29</td>
<td>96.54</td>
</tr>
<tr>
<td><strong>Panel B: Long-Run Parameter Estimates</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GINI = 0.341 − 0.213 EF − 0.261 Y − 0.595 EDUC + 0.152 POP</td>
<td>(11.50)*</td>
<td>(−14.80)*</td>
<td>(−7.59)*</td>
</tr>
<tr>
<td>$\quad \quad \quad \quad \quad (−12.90)* \quad \quad \quad \quad (10.10)*$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adj. $R^2 = 0.49$ LM = 1.24 HE = 1.21</td>
<td>[0.31]</td>
<td>[0.27]</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Larsson, Lyhagen, and Löthgren (2001) cointegration procedure denoted by LLL. $t$-Statistics and probability values are reported in parentheses and brackets, respectively. LM is the Lagrange multiplier test for serial correlation. HE is White’s heteroscedasticity test.

*Significance at 1%; **significance at 5% level.

\[
\Delta \text{POP}_{it} = \xi_{5j} + \sum_{k=1}^{q} \psi_{51k} \Delta \text{GINI}_{it-k} + \sum_{k=1}^{q} \psi_{52k} \Delta Y_{it-k}
\]
\[
+ \sum_{k=1}^{q} \psi_{53k} \Delta \text{EDUC}_{it-k} + \sum_{k=1}^{q} \psi_{54k} \Delta \text{POP}_{it-k}
\]
\[
+ \sum_{k=1}^{q} \psi_{55k} \Delta \text{EF}_{it-k} + \lambda_{5i} e_{iit-1} + u_{5it}
\]

where $\Delta$ is the first-difference operator, $k$ is the lag length set at 2 based on likelihood ratio tests, and $u$ is the serially uncorrelated error term. With respect to Equations (3a–3e), short-run causality is determined by the statistical significance of the partial $F$-statistic associated with the corresponding right-hand-side variables. Long-run causality is revealed by the statistical significance of the respective error correction terms using a $t$ test.

Table 4 displays the results for the panel error correction model. Equation (3a) reveals that economic freedom has a negative and statistically significant impact on income inequality in the short run. As mentioned above, Berggren (1999) suggests that implementing policies toward economic freedom may increase income inequality in the short run due to redistribution benefiting the rich, but in the long run economic freedom may benefit the poor due to economic growth. According to our results, economic freedom reduces income inequality both in the short and in the long run. In terms of the impact of income on income inequality, our findings of a negative relationship parallel the results reported by Ashby and Sobel (2008). With respect to the impact of education on income inequality, Knight and Sabot (1983) argue that the total effect of education on income inequality can be decomposed into two effects: composition and compression effects. The composition effect raises the relative size of the educated population and tends to raise income inequality initially, but eventually lowers income inequality. The compression effect, on the other hand, lowers income inequality since the return on education decreases as the relative supply of educated people increases. Hence, the effect of education on income inequality depends on the relative strength of the composition and compression effects. Previous empirical studies find a negative relationship between education and income inequality in developed countries (Becker and Chiswick 1966; De Gregorio and Lee 2002) which our results confirm. Finally, we find a positive relationship between population and income inequality which supports the findings of Ram (1984).

From Equation (3b), income inequality has a negative and statistically significant impact on economic freedom while per capita income, education, and population each have a positive
and statistically significant impact in the short run. In other words, there is bidirectional Granger-causality between economic freedom and income inequality in the short run. This result is not surprising given that in democratic countries like the United States high income inequality forces governments to follow policies redistributing income from the rich to the poor. Such redistributive policies induce economic freedom to decline in all three areas: government spending, taxation, and labor market freedom. As for the control variables, the positive relationship between per capita income, education, and population is not surprising either. As per capita income increases more people are likely to support policies toward more economic freedom since they have more to lose from government intervention. Education affects economic freedom most likely via an income channel.

In terms of Equation (3c) economic freedom, education, and population each have a positive and statistically significant impact on income while income inequality has a negative and statistically significant impact in the short run. As mentioned above, there is an extensive literature analyzing the relationship between economic freedom and the growth rate of income. According to Gwartney, Lawson, and Holcombe (1999) and Berggren (2003), economic freedom promotes growth via several channels. First, low taxation creates incentives for investment. Second, less regulation in labor markets leads to more efficient allocation of human capital. Our results support the findings by Scully (2002), Carlsson and Lundstrom (2002), Pitlik (2002), and Weede and Kampf (2002) of the positive impact of economic freedom on per capita income. As Partridge (2005) argues, the evidence on the relationship between income inequality and growth is conflicting. Greater income inequality may lead to greater savings and thus greater capital accumulation and higher growth (Kaldor 1957; Pasinetti 1962). But it may also lead to higher taxes and lower growth (Alesina and Rodrik 1994). Several cross-country studies such as Perotti (1996) find a negative relationship between income inequality and growth. Nevertheless, using panel data, Li and Zou (1998) and Forbes (2000) find that increases in income inequality are positively associated with growth in the short run. Our results yield a negative relationship between income inequality and per capita income lending support for the findings of Alesina and Rodrik (1994) and Perotti.

Equation (3d) reveals that economic freedom and income each have a positive and statistically significant impact on education, whereas income inequality and population each have a negative and statistically significant impact in the short run. The impacts of economic freedom and income inequality on education are not trivial. To our knowledge, the literature is void of any studies analyzing the relationship between economic freedom and education. Returns to investment in education are positively related

<table>
<thead>
<tr>
<th>Sources of Causation (Independent Variables)</th>
<th>Dependent Variable</th>
<th>ΔGINI</th>
<th>ΔEF</th>
<th>ΔY</th>
<th>ΔEDUC</th>
<th>ΔPOP</th>
<th>ΔECT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short Run</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(3a) ΔGINI</td>
<td>—</td>
<td>51.26 (−0.015)</td>
<td>25.29 (−0.063)</td>
<td>76.11 (−0.058)</td>
<td>31.62 (0.168)</td>
<td>−0.231</td>
<td></td>
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<td>(3b) ΔEF</td>
<td>31.25 (−0.578)</td>
<td>—</td>
<td>30.92 (0.313)</td>
<td>29.59 (0.051)</td>
<td>30.94 (0.052)</td>
<td>−0.386</td>
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<td>(3c) ΔY</td>
<td>94.50 (−0.579)</td>
<td>36.64 (0.050)</td>
<td>—</td>
<td>15.09 (0.145)</td>
<td>74.43 (0.032)</td>
<td>−0.206</td>
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<td>(3d) ΔEDUC</td>
<td>94.90 (−0.090)</td>
<td>40.95 (0.814)</td>
<td>27.11 (0.058)</td>
<td>—</td>
<td>57.39 (−0.139)</td>
<td>−0.533</td>
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<td>(3e) ΔPOP</td>
<td>0.13 (−0.216)</td>
<td>95.30 (0.166)</td>
<td>45.32 (0.702)</td>
<td>30.99 (−0.296)</td>
<td>—</td>
<td>−0.020</td>
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Notes: Partial F-statistics reported with respect to short-run changes in the independent variables. The sum of the lagged coefficients for the respective short-run changes is denoted in parentheses. ECT represents the coefficient of the error correction term. Probability values are in brackets and reported underneath the corresponding partial F-statistic and sum of the lagged coefficients, respectively.

*Significance at 1%; **significance at 5% level.
to how well the property rights are protected. Economic freedom creates incentives to invest in education via creating an economic environment in which property rights are protected. Our results support this argument. Bjornskov (2009) argues that income inequality affects education via two different channels. On the one hand, income inequality lowers investment in education due to credit constraints faced by the lower income individuals while income inequality creates incentives for lower and middle income individuals to invest in education. According to our results, the negative effect of inequality on education is stronger.

Finally, in terms of Equation (3e) income and economic freedom each have a positive and statistically significant impact on population; education has a negative and statistically significant impact; and income inequality has a statistically insignificant impact in the short run. In terms of the long-run dynamics based on the error correction terms from Equations (3a–3e), income inequality, economic freedom, income, education, and population each respond to deviations from long-run equilibrium given the statistical significance of the respective error correction terms. According to Equations (3a) and (3b), the speed of adjustment toward long-run equilibrium is faster for economic freedom than income inequality. While it is approximately 4 years for income inequality, it is less than 3 years for economic freedom. Focusing on the relationship between income inequality and economic freedom, the long-run dynamics confirm the bidirectional Granger-causality found in the short-run dynamics.

V. CONCLUDING REMARKS

We investigate the causal relationship between income inequality and economic freedom both in the short and the long run using data from U.S. states over the period 1981 to 2004. Unlike previous studies which implicitly assume unidirectional causality from economic freedom to income inequality, we explicitly examine the Granger-causal dynamics between income inequality and economic freedom within a panel error correction model framework. The results from the Larsson, Lyhagen, and Löthgren (2001) panel cointegration procedure reveal a long-run relationship between income inequality, economic freedom, income per capita, education, and population. The long-run equilibrium equation shows that economic freedom has a negative impact on income inequality. The panel error correction model results indicate bidirectional Granger-causality between income inequality and economic freedom in both the short and the long run. These results suggest that high income inequality may cause states to implement redistributive policies causing economic freedom to decline. As economic freedom declines, income inequality rises even more. In other words, it is quite possible for a state to get caught in a vicious circle of high income inequality and heavy redistribution. In addition, our results also support previous studies which find a positive relationship between economic freedom and per capita income.

As an avenue for further research, the relationship between economic freedom and education is worth investigating. The literature thus far appears to ignore the role of economic freedom in the creation of human capital, but rather focuses on its role on the creation of physical capital.12

REFERENCES


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