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BLUEPRINT MISSISSIPPI: A BLUEPRINT FOR INCOME INEQUALITY AND LOWER ECONOMIC GROWTH IN URBAN AND DELTA REGION COUNTIES?

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Summary

Blueprint Mississippi includes policy recommendations that if implemented successfully, would increase the the number of Mississippians employed in the high technology industry. To the extent that growth in the high technology industry characterizes a process of skill-biased technological change, job growth in this sector can engender earnings and income inequality. We examine employment in Mississippi's information technology sector–a particular segment of the high technology industry—and the effect it has on household income inequality at the county level. Our analysis suggests that employment growth in the information technology sector increases household income inequality for urban and Delta region counties. The increases in household income inequality engendered by job growth in the information technology sector also reduces the growth rate of county income. Our results suggest that successful implementation of Blueprint Mississippi policy recommendations for increasing the employment share of high technology in the state will have, at least in the short run, an adverse affect on urban and Delta region counties.

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Blueprint Mississippi (2004) provides a set of policy recommendations that would enable the development of the Mississippi regional economy toward a so-called "New Economy".[1] As Atkinson and Court (1999) describe it, a "New Economy" is a knowledge and idea-based economy where innovative ideas, knowledge, and technology drive job creation and higher living standards. The policy framework articulated by Blueprint Mississippi could not be more relevant, timely or urgent, as Mississippi ranks last overall in a ranking of states based on criteria that characterize the extent to which a given state economy is a "New Economy" (Atkinson, Court, and Ward; 1998).

Of the more than 50 recommendations provided by Blueprint Mississippi, one particular New Economy type goal is to diversify and improve the economic base of Mississippi by increasing the percentage of employees in high technology industries. One of the characteristics of the so-called "New Economy" is that from the mid-1990s, economic growth has been accompanied by substantial investments and innovations in computer technology. Gordon (2000) for example, reports that more than half of the surge in labor productivity in the late 1990s had its origin in the production of computer hardware, peripherals, and telecommunications equipment—information technology–with some spillover to the small segment of the economy producing durable goods. This suggests that the engine of productivity growth in the so-called high technology industry has been the information technology sector. In general, the productivity increases emanating from the high technology industry appears to have its source in that sector responsible for the production of so-called information technology.

To the extent that productivity increases in a particular sector characterize a process of skill-biased technological change, increases in the productivity of workers in information technology would increase their earnings relative to workers in other sectors. As such, the productivity increases witnessed in the production of information technology could be a causal factor underlying earnings inequality in the U.S economy. The economics literature has produced many analyses of earning inequality, however most of these studies are at the national level, and seem to have ignored the consequences of the productivity revival in the information technology sector.[2] The general conclusion of much of this literature is that at least since

[1] *Blueprint Mississippi* is a private sector sponsored strategic plan for economic development in the state of Mississippi. It includes more than 50 policy recommendations that range from expanding and improving pre-kindergarten education to improving the state's highway, rail, air and seaport capabilities. A copy of the report can be obtained from the Mississippi Economic Council at http://www.msmed.com/mechw .

[2] Empirical analyses of earnings inequality include those by Card & Dinardo (2000), Galor and Moav (2000), and Johnson (1997)

the 1908s, the U.S economy has seen the earnings of those at the top end of the skill distribution increase, relative to those at the bottom of the skill distribution.

From a public policy perspective, the existence of earnings inequality matters if economic growth itself depends upon earning inequality.While there is evidence that inequality can be beneficial for economic growth (Li and Zou, 1998), the majority of the empirical evidence suggests that inequality is harmful for, and reduces economic growth (Aghion, Caroli, and Garcia-Penalosa, 1999). Thus, if economic growth is a policy goal, the existence of earnings inequality can constrain the welfare gains normally associated with higher per capita output, placing a given economy on a lower and suboptimal equilibrium growth path. In this context, active development policies that seek to foster growth through cultivating particular skill-intensive industries, could actually lower growth as a result of such industries engendering levels of earnings inequality that reduce economic growth.

Below, we consider the effects that employment growth in the high technology industry—the kind advocated in Blueprint Missssissippi— has on inequality and economic growth in Mississippi. A cross-county approach is utilized to examine how sensitive household income inequality in Mississippi is to changes in the employment share of the information technology sector—a particular segment of the high technology industry that appears to be be a major source of productivity gains for the industry as a whole. Our results suggest that in the state of Mississippi, household income inequality is sensitive to, and increases with respect to the number of workers employed in the information technology sector. Household income inequality also appears to reduce the growth rate of income in urban and Delta region counties. Our findings suggest that if Blueprint Mississippi recommendations for attracting skill-intensive high technology firms are successfully implemented, urban and Delta counties will experience higher household income inequality and lower income growth.

Income Inequality In Mississippi

While there are many measures of income inequality, data limitations in Mississippi county-level economic data best permit a consideration of the ratio of median to average household income.[3] Theoretical justifications for using the ratio of median to average household income as a measure of income inequal-

[3]Other measures of income equality include the Gini coefficient (Deininger and Squire, 1996), and measurement of income shares accruing to select quintiles in a distribution (Persson and Tabellini, 1994).

ity follow from Persson and Tabellini (1994) and Gloom (2004). The essential idea is that if income is distributed normally, say based upon some underlying normal distribution of ability/skills, the mean and median income would be identical. When ability/skills are not normally distributed or skewed, the mean departs from the median, and the underlying income distribution is skewed, or unequal. In general, the closer the ratio of median to mean household income is to unity, the more equal is the distribution of household income.

Table 1 reports by rank for the 82 counties in Mississippi the ratio of median to mean household income (φ) based on 2000 Census Data. Given the measure of household income inequality φ, De Soto county has the most equal distribution of income by household, and Humphreys county has the least equal distribution. Table 1 also identifies counties as being either urban and/or being located in the Mississippi Delta—a historically and chronically poor region of the state.[4] As a group, urban counties in Mississippi have higher income equality relative to all other counties in the state, as their group median φ exceeds that for the entire state. In general, Delta counties are below the county median value of φ—suggesting that counties located in the Mississippi Delta region are not particularly egalitarian places to live in—at least in terms of the distribution of household income. Nonetheless, if sensible measures of social welfare—a measure of average household wellbeing—are a function of the distribution of household income, households in the Mississippi Delta region counties are not as well-off relative to other Mississippi counties.

The range of φ is approximately 36 percent–which represents significant variation across the counties. To the extent that variation in φ is explained by county-level variations in the labor market skills of workers, the dispersion in φ across the counties could reflect differential demands for skilled workers in sectors where there is a skill premium. In this context, counties that rank low in terms of Δ have labor markets characterized by a dualism in which there is a significant percentage of unskilled workers earning low wages, and a percentage, not necessarily significant, of skilled workers earning high wages. This is more generally viewed as inequality engendered by skill-biased technological change, and empirically has been associated with the growth of "New Economy" industries such as information technology. As Blueprint Mississippi provides policy recommendations that would induce growth in the information technology sector, it is conceivable that job growth in the information technology sector could engender income inequality. If inequality in turn is harmful for economic growth, job growth in skill-intensive sectors such as information technology

[4]A county is identified as being urban according to the U.S Department of Agriculture's classification (Cook and Mizer, 1994). Counties in the Delta region of the state were identified on the basis of the classification provided by Doolittle and Davis (1996).

would undermine policy goals oriented toward income growth.

Explaining Income Inequality in Mississippi

To what extent is the household income inequality depicted in Table 1 explained by the distribution of jobs, and the associated earnings between the information technology and other sectors in the state of Mississippi? We explore this by considering, following VanHoudt (2000), the following Cobb-Douglas type specification of inequality:

$$\varphi_i = (aw_t)^{\lambda_t}\,((1-a)w_o)^{-\lambda_o} \tag{1}$$

where φ_i is a measure of household earnings inequality in the ith county, a is the fraction of workers employed in the information technology sector, w_t are the wages earned in the information technology sector, 1 - a is the fraction of workers employed in all other sectors, w_o are the wages earned in all other sectors, λ_t is the elasticity of inequality with respect to the wage of workers in the information technology sector, and λ_o is the elasticity of inequality with respect to the wage of workers in all other sectors.

The specification of household earnings inequality in equation (1) is, by itself definitional—-it defines inequality as the ratio of the earnings of workers in the information technology to workers in other sectors. As the ratio φ increases, it is simply measuring the increased earnings share of workers in the information technology sector. Nonetheless, the specification of φ is silent on what measure of income inequality to utilize. Our strategy is to measure φ as the ratio of median to mean household income, and to estimate a log specification, where, since we cannot observe sector-specific earnings, the earnings shares are approximated with sector-specific employment shares. We estimate the following logarithmic specification of equation (1):

$$\begin{aligned} ln\ \varphi_i &= \beta_0 + \beta_1 URBAN_i + \beta_2 DELTA_i \\ &+ \beta_3\ ln\ INFTECH_i + \beta_4\ ln\ OTHER_i + \epsilon_i \end{aligned} \tag{2}$$

where $URBAN_i$, is a dummy variable indicating whether or not the ith county is urban, $DELTA_i$ is a dummy variable indicating whether or not the ith county is in the Mississippi Delta, $INFTECH_i$ is the percentage of workers in the ith county employed in the information technology sector, $OTHER_i$ is the percentage of workers in the ith county employed in all other sectors, and ϵ_i is an error term.

The inclusion of dummies for a county being urban or located in the Mississippi Delta region mitigates any unobserved heterogeneity that could potentially bias the parameter estimates—as the econometrician is never completely sure as to what unobserved factors are important for explaining a regressand of interest. The sign and magnitude of β_3 is our primary interest. If there is skill-biased technological change in the information technology sector, such that the earnings of workers there are increasing relative to workers in other sectors, then β_3 should have a negative sign ($\beta_3 < 0$). Mississippi county employment share data for $INFTECH$ and $OTHER$ were obtained from the U.S Census Bureau's County Business Patterns 2000 - 2001.

Our estimation of the household inequality specification in equation (2) proceeds by recognizing it's inherent multicollinearity, and the possibility of parameter heterogeneity. The nature of the inequality specification is such that the employment shares are more or less exact linear combinations of each other. As such, inference on parameter estimates with the employment shares as specified would be undermined by the large standard errors that result from multicollinearity. To circumvent this, we orthogonalize the employment shares with the Gram-Schmidt method (Saville and Wood, 1991), and use the orthogonalized values of $ln\ INFTECH$ and $ln\ OTHER$ as regressors.[5] The specification of household income inequality in equation (2) also generates a conditional distribution of household income inequality across Mississippi counties. As the distribution of income can be skewed, Ordinary Least Squares (OLS) estimation of equation (2) could obscure the possibility that the independent variables have a differential impact, depending upon what position in the conditional distribution a county occupies. To accommodate the possible existence of this type of parameter heterogeneity across counties, we estimate the specification in (2) both within an OLS and a quantile regression framework.[6]

Table 2 reports the OLS and quantile regression parameter estimates for the household inequality speci-

[5]The Gram-Schmidt procedure essentially subtracts the vector of linearly dependent variables from their projection, creating an orthogonal vector. Each element in this orthogonal vector represents the original independent variables minus the linear influences of their combinations.

[6]For a conditional mean relationship $y_i = x_i'\beta_i + \mu_i$, a quantile regression model (Koenker and Bassett, 1978; Koenker and Hallock , 2001) minimizes for some quantile τ, where $0 < \tau < 1$, the following function:

$$\sum_{i=1}^{n} \rho_\tau(y_i - x_i'\beta_i)$$

where for binary indicator function $I(\cdot)$, $\rho_\tau = \mu[\tau$ - $\mathrm{I}(\mu < 0)]$. Solving this problem differs from OLS in that instead of minimizing the sum of squared residuals (e.g, where $\rho_\tau = y_i$ - $x_i'\beta_i$), the sum of asymmetrically weighted absolute-valued residuals is minimized.

fication of equation (2). For the 82 Mississippi counties under consideration, complete data on employment shares in the information technology sector could only be obtained for 60 counties. A given household income inequality quantile is defined such that if a given county is in the τth quantile, it's value of φ_i is higher (e.g., it has less income inequality) than a proportion τ of the counties in Mississippi, and less (e.g., it has more income inequality) than a proportion (1 - τ) of counties in the state of Mississippi. The quantile regression parameter estimates are reported across 19 quantiles starting with the $\tau = .95$ quantile , and decreasing in increments of .05, ending with the $\tau = .05$ quantile. For the OLS parameter estimates, robust heteroskedastic-consistent standard errors are reported, and R^2 is reported for both the OLS and quantile estimates as a goodness-of-fit measure.[7]

For the OLS parameter estimates in the first column of Table 2, all variables are significant except for the share of county employment in all other sectors outside of information technology. The significant and negative sign on the share of employment in the information technology sector suggests that employment growth in this sector increases county level household income inequality—as a lower value of φ is an indication of higher household income equality. Given the possibility of parameter heterogeneity across the conditional distribution of φ, the remaining columns of Table 2 report parameter estimates for 19 quantiles. For a majority of the quantiles, the sign on the share of employment in the information technology sector is negative and significant, and has the largest magnitude for Mississippi counties in the 65th and 60th quantile of the conditional distribution of household income inequality. The consistency of the sign and/or significance of the effects of the share of employment in the information technology sector on household income inequality does suggest robustness, and that the effects are reasonably identified.

The significance of URBAN and DELTA in the OLS, and several of the quantile parameter estimates suggest that there is something different about Mississippi counties that are urban and/or located in the Delta region of the state. It is not obvious what is different about such counties–however such differences could be important for how the share of employment in the information technology sector engenders household earnings inequality. To explore this possibility, Table 3 reports parameter estimates that interacts URBAN and DELTA with the technology employment share in the household income inequality specification of equation (2). The OLS parameter estimates reveal that the singular effects of employment shares are no longer significant after the county information technology share is interacted with URBAN and DELTA.

[7] For quantile regression parameter estimates, the interpretation of R^2 differs from that of OLS. Whereas for OLS, R^2 measures goodness-of-fit over the entire conditional distribution of the dependent variable, in a quantile regression it measures goodness-of-fit for a particular quantile—or a subset of the conditional distribution (Koenker and Machado, 1999).

Instead, increases in the information technology employment share for a county increases inequality only for urban Mississippi counties. While the effect is negative for counties in the Delta region, it is not significant when the effect is estimated via OLS.

For the entire conditional distribution of household income inequality, the quantile parameter estimates in Table 3 suggest that it is indeed the case that the effects of information technology employment shares on household income inequality matters for Mississippi counties that are urban and/or located in the Delta region. Across the quantiles the urban and Delta region effect is negative and significant in across a sizable portion of the conditional distribution of household income inequality. What's instructive is that while the singular effects of the employment shares are negative across a sizable portion of the conditional distribution of household income inequality—such effects are never significant. This suggests that in Mississippi, the causal nexus between household income inequality and skill-biased technological change manifests itself through higher earnings inequality in urban and Delta region counties.

Household Income Inequality and Growth in Mississippi

The results in Tables 2 - 3 identify a presumably causal effect of employment growth in Mississippi's information technology sector–which can be a manifestation of skill-biased technological change—and household income inequality at the county level. From a welfare standpoint, income inequality could matter for two basic reasons. Inequality could matter for the well-being of individuals if what matters to them is where they stand, in terms of income and wealth, relative to others (Cole, Mailath, and Postlewaite, 1995). Household income inequality could also affect the underlying saving/investment behaviors responsible for economic growth–which determines how much income/wealth is available to a given individual. It is in this second context that the effects of inequality can be explored empirically, as the theory and empirics of economic growth easily lend themselves to a consideration of what impact, if any, does income inequality have on the growth of income and output.

As we do not have data on county level output, we consider the effect that inequality has on the growth of county income. This provides a useful approximation, as income and output—the goods and services produced at the county level—are proportional to one another. Our approach is the partial adjustment framework, which presumes that there is some long-run steady-state or equilibrium level of income for each county that is a function of some exogenous factors.[8] Let I(0) and $I^* = \sum \beta_i X_i + \mu$ be initial and steady-state income respectively, where the X_i are exogenous factors that determine the steady-state level of income, and μ is an error term. Given actual income at time t of I[(t)], by approximating about the steady-state, where d$ln[I(t)]$/dt = $\lambda[ln(I^*)$ - ln[I(0)] a regression specification for cross-county variation in the level of income is:

$$ln[I(t)] - ln[I(0)] = -\theta\ ln[I(0)] + \theta \sum \beta_i X_i + \theta\mu$$

where $\theta = 1$ - $exp(-\ \lambda t)$, and λ is the rate at which income converges to its steady-state value.

Our empirical analogue of the regression specification implied by the partial adjustment model of county level income growth above is:

$$\begin{aligned} ln\ I00_i - ln\ I90_i &= \beta_0 + \beta_1 I90 + \beta_2 ln\ \varphi_i + \beta_3\ URBAN_i \\ &+ \beta_4\ DELTA_i + \beta_5\ URBAN_i \times ln\varphi_i + \beta_6\ DELTA_i \times ln\varphi_i + \mu_i \end{aligned} \tag{3}$$

where ln $I00_i$ - ln $I90_i$ is the difference in the log of income—or the growth rate of income—in the ith county between the years 2000 and 1990. County income data were obtained from the U.S Census Bureau's County Business Patterns 2000 - 2001. The empirical specification of county level income growth in equation (3) views departures from the steady-state level of income as a function of the level of household income inequality as measured by φ along with its interaction with a county being urban and/or located in the Delta region. As such, parameter estimates will permit a determination as to what effect county level household income inequality has on income growth, and whether or not the its effect is different for urban and Delta region counties.

Our strategy for estimating the income growth specification in equation (3) parallels our estimation strategy for the household income inequality specification. We allow for the possibility that there is parameter heterogeneity, in that the effect of the exogenous variables that determine the steady-state level of county income may differ across counties in Mississippi. As Mello and Perrelli (2003) indicate, such heterogeniety is likely given that unconditional growth distributions have long right tails, and that the effects of exogenous variables on growth rates could in principle depend upon the growth rate. A comparison of

[8] The partial adjustment framework is a popular method for empirically estimating the parameters of neoclassical growth models. For an example see Mankiw, Romer and Weil (1992).

OLS with quantile regression parameter estimates also lends insight into robustness. OLS estimates are appropriate when the error term is homoskedastic, whereas quantile regression estimates allow for departures from homoskedasticity. Thus, a comparsion of OLS and quantile regression estimates provide for a check on the true sign and magnitude of a particular exogenous variable on the growth rate across the conditional growth distribution for Mississippi counties.

Table 4 reports the OLS and quantile regression parameter estimates of the income growth specification in equation (3). The OLS estimates suggest that that in Mississippi, county income growth and the level of household income inequality are positively related. Or, since higher levels of φ are associated with higher levels of income equality—income inequality is apparently beneficial for income growth in the state of Mississippi. However, the positive sign on the interaction of household income inequality with being an urban and/or Delta region county suggests that for these type of counties, household income inequality is harmful for income growth. The insignificance of $I90$ suggest that, at least for the time period under consideration, initial income does not matter for income growth. While being an urban and/or Delta region economy has a positive impact on income growth, it is only significant for urban counties.

The quantile parameter estimates in Table 4 reveal a pattern of sign and significance for a significant part of the entire conditional income income growth distribution for Mississippi counties that is similar to the OLS estimates. The exception being that for 5 of the quantiles, being a Delta region county has a positive and significant effect on income growth, and initial income matters for counties in the 95th quantile. In terms of magnitude, income inequality is most beneficial for income growth for counties in the 95th quantile, most harmful for urban counties in the 30th quantile, and most harmful for Delta region counties in the 85th quantile. The similarity between the OLS and quantile parameter estimates of the income growth specification in equation (3) suggest that the effects of household income inequality are well-identified, as the OLS estimates are robust with respect to heteroskedasticity, and the quantile estimates are robust with respect to outliers, and across the conditional distribution of income, allows for parameter heterogeneity–and there are no sign reversals for significant parameter estimates.

Policy Implications

Our analysis of the determinants of household income inequality, and the effect of household income inequality on growth in the state of Mississippi provide a cautionary warning for Blueprint Mississippi policy recommendations that if implemented, would presumably catalyze employment growth in the technology sector. We find that employment growth in the information technology sector increases household income inequality at the county level, and for counties that are urban and/or located in the Delta region, increasing levels of household income inequality reduce income growth. To the extent that sensible measures of economic welfare include individual relative income shares, and income growth, Mississippi residents that live in urban and/or Delta region economies could be made worse off if the Blueprint Mississippi policy recommendations for catalyzing employment growth in the technology sector are successfully implemented.

The explicit recommendations of Blueprint Mississippi establish technology sector employment share targets of 3.6 percent, and 4.5 percent in the years 2010 and 2015 respectively. In our sample of Mississippi counties, the average employment share in the information technology sector is 1.3 percent—-significantly below the recommended targets. What would be the effect on household income inequality of say, increasing the employment share of information technology by approximately 177 percent, from 1.3 to 3.6 percent—the Blueprint Mississippi 2010 target? We can benchmark this by considering the effects for the quantile with the largest coefficient in Table 3, for illustrative purposes. Ceteris paribus, a 177 percent increase in the information technology employment share would increase household income inequality–a decrease in the ratio of household median to average income—by approximately 29.5 percent for urban counties in the 90th percentile of the conditional household inequality distribution. For Delta region counties, the corresponding increase in household income inequality is approximately 24.1 percent for counties in the 35th quantile of the conditional household inequality distribution.[9]

What would be the effect of increasing the employment share of information technology by 177 percent on county income growth? As this would increase household income inequality in urban and Delta region counties, the effects of increases in household income inequality on the growth of county income can be benchmarked in a similar fashion by considering from the quantile regression parameter estimates in Table 4, the largest absolute valued coefficient on the interactions of URBAN and DELTA with φ, and the associated quantiles. Ceteris paribus, a 29.5 percent increase in household income inequality would reduce income growth by approximately 25 percent for urban counties in the 30th quantile of the conditional income growth distribution. For counties in the Delta region, a 24.1 percent increase in household income inequality would reduce income growth by approximately 5.4 percent for Delta region counties in the 85th

[9]These estimates follow from simple computations of the elasticity of inequality with respect to changes in the information technology share from the largest in absolute value quantile regression parameter estimates in Table 3—evaluated when both URBAN equals unity and DELTA equals unity.

quantile of the conditional income growth distribution.[10]

Our illustrative benchmark estimates of the effects of increasing the employment shares in information technology across Mississippi are instructive. They suggest that urban and Delta region counties would fare poorly if the recommendations of Blueprint Mississippi advocating employment growth in the high technology sector were successfully implemented. Apparently, in urban and Delta region counties, the distribution of household income is particularly sensitive to the household distribution of skills necessary for employment in the information technology sector. The sensitivity of income to the distribution of skills probably underscores a significant mismatch between the actual endowment of household skills, and those skill endowments required for employment in the information technology sector. Such skill mismatches are characteristic of labor markets experiencing skill-biased technological change. In this context, our findings that Blueprint Mississippi's policy recommendations for encouraging employment growth in the high technology sector are not entirely pessimistic. To the extent that skill mismatches in urban and Delta region economies can be remedied with appropriate human capital policies, growth in information technology employment shares need not have deleterious effects on household income inequality and income growth.

Of course, Blueprint Mississippi does indeed make human capital policy recommendations, that if implemented, could possibly address the skill disparities that engender household income inequality. These recommendations include policy interventions that would increase participation in lifelong learning, retrain dislocated workers, increasing the percentage of children enrolled in prekindergarten, increase per-pupil expenditures, and increase the number of certified teachers. Such human capital policy interventions take time to be implemented and made effective.In contrast, the use of say, tax and infrastructure subsidies to attract firms can be implemented and made effective in a much shorter period of time. Given such policy effectiveness lags, it is likely that at least in the short-run, urban and Delta region counties will fare poorly if Blueprint Mississippi policy recommendations for increasing the share of employment in the high technology sector are successfully implemented. If in the long-run, Blueprint Mississippi human capital policy recommendations are implemented successfully so as to eliminate the skill disparities that engender household income inequality, urban and delta region counties need not fare poorly as Mississippi increases employment shares in high technology sectors such as information technology.

[10] These are estimates of the elasticity of income growth with respect to changes in household income inequality based on the quantile regression parameters in the 30th quantile for urban counties, and the 85th quantile for Delta region counties.

Conclusion

Our analysis suggests that successful implementation of Blueprint Mississippi policy recommendations for increasing the high technology industry employment share in the state seems likely to have, at least in the short run, an adverse effect on urban and Delta region counties. This conclusion follows from a consideration of the effect of increases in the employment share of the information technology sector—a particular segment of the high technology industry—on household income inequality at the county level in Mississippi. Increases in household income inequality were also found to reduce income growth for urban and Delta region counties. From a welfare perspective, our results suggest that increases in the employment share of the high technology industry would render urban and Delta region economies worse-off, as employment growth in the information technology sector would lower the relative income status and growth of income for urban and Delta region households.

As a policy recommendation, the notion that Mississippi should increase the share of state employment in the high technology industry is not in itself inconsistent with improving household welfare through higher and growing incomes. Our analysis suggests that such a policy will not improve the economic welfare of Misissippians in urban and Delta regions in the absence of human capital policies that remedy any labor force skill deficits needed for employment in the high technology industry. If the human capital policy recommendations of Blueprint Mississippi are implemented effectively so as to endow all, or a sizable fraction of the labor force in urban and Delta region counties with the skills requisite for employment in the high technology industry, there need not be any significant income inequality or suboptimal income growth associated with employment growth in the high technology industry.

Table 1
Year 2000 Rankings of Mississippi Counties
By Household Income Inequality (φ)

County	φ	**Rank**	**County**	φ	**Rank**	**County**	φ	**Rank**	**County**	φ	**Rank**
De Soto[a,b]	.704	1	Tishomingo	.680	2	Prentiss	.673	3	Lamar[a]	.670	4
Pontotoc	.667	5	Issaquena[b]	.665	6	Perry	.658	7	Choctaw	.651	8
Rankin[a]	.649	9	Itawamba	.644	10	Pearl River	.641	11	Union	.639	12
Monroe	.638	13	Alcorn	.628	14	Greene	.627	15	Hancock[a]	.626	16
Clarke	.626	17	Amite	.626	18	Oktibbeha	.617	19	Franklin	.616	20
Lafayette	.607	21	George	.594	22	Jackson[a]	.592	23	Tippah	.590	24
Benton	.585	25	Carroll[b]	.584	26	Winston	.579	27	Stone	.577	28
Yalobusha	.574	29	Jasper	.571	30	Chickasaw	.568	31	Covington	.566	32
Panola[b]	.563	33	Jefferson	.561	34	Madison[a]	.557	35	Wayne	.557	36
Marshall	.556	37	Lincoln	.556	38	Lowndes	.555	39	Calhoun	.555	40
Lee	.552	41	Tate[b]	.552	42	Lawrence	.549	43	Simpson	.547	44
Grenada	.545	45	Harrison[a]	.543	46	Clay	.541	47	Webster	.533	48
Smith	.530	49	Jefferson Davis	.528	50	Neshoba	.522	51	Copiah	.522	52
Forrest[a]	.522	53	Attala	.521	54	Lauderdale	.518	55	Newton	.516	56
Walthall	.504	57	Tallahatchie[b]	.501	58	Warren[b]	.498	59	Montgomery	.495	60
Jones	.493	61	Scott	.493	62	Marion	.492	63	Wilkinson	.487	64
Kemper	.487	65	Hinds[a]	.484	66	Adams	.483	67	Pike	.478	68
Leake	.469	69	Quitman[b]	.468	70	Washington[b]	.456	71	Noxubee	.455	72
Claiborne	.445	73	Sharkey[b]	.443	74	Bolivar[b]	.438	75	Yazoo[b]	.417	76
Tunica[b]	.415	77	Sunflower[b]	.411	78	Leflore[b]	.408	79	Coahoma	.401	80
Holmes[b]	.386	81	Humphreys[b]	.386	82						

Notes:

As a measure of income inequality, φ is the ratio of median household to mean household income. Household median and mean income were constructed from data reported in the U.S. Census Bureau's *City and County Data Book:* 2000.

[a] Urban County

[b] Delta County

Table 2
OLS And Quantile Parameter Estimates:
Equation (2)

Specification:	*OLS* [e]	τ =.95	τ =.90	τ =.85	τ =.80	τ =.75	τ =.70	τ =.65	τ =.60	τ =.55
Variable:										
CONSTANT	-.598	-.416	-.452	-.465	-.479	-.484	-.518	-.559	-.576	-.585
	$(.020)^a$	$(.017)^a$	$(.027)^a$	$(.030)^a$	$(.043)^a$	$(.032)^a$	$(.035)^a$	$(.036)^a$	$(.038)^a$	$(.033)^a$
URBAN	.105	.221	.215	.064	.068	.069	.119	.074	.084	.093
	$(.047)^a$	$(.025)^a$	$(.034)^a$	(.075)	(.096)	(.081)	(.083)	(.083)	(.087)	(.074)
DELTA	-.159	-.188	-.142	-.111	-.107	-.219	-.174	-.158	-.158	-.149
	$(.040)^a$	$(.020)^a$	$(.031)^a$	$(.057)^b$	(.085)	$(.067)^a$	$(.070)^a$	$(.068)^b$	$(.071)^b$	$(.062)^c$
ln INFTECH[d]	-.046	-.071	-.052	-.015	-.038	-.035	-.016	-.068	-.071	-.071
	$(.026)^c$	$(.013)^a$	$(.015)^a$	(.024)	(.038)	(.031)	(.034)	(.045)	$(.038)^c$	$(.031)^b$
ln OTHER[d]	.038	.069	.032	-.015	.002	-.003	-.041	.020	.045	.045
	(.038)	$(.014)^a$	(.029)	(.034)	(.047)	(.039)	(.045)	(.062)	(.054)	(.045)
N	60	60	60	60	60	60	60	60	60	60
R^2	.297	.134	.108	.129	.137	.136	.129	.129	.133	.134

Notes:
Standard errors in parentheses.
N = Number of observations.
[a] Significant at the .01 level
[b] Significant at the .05 level
[c] Significant at the .10 level
[d] Log of Gram-Schmidt orthogonalized value of variable
[e] Robust standard errors

Table 2—-continued
OLS And Quantile Parameter Estimates:
Equation (2)

Specification:	τ =*.50*	τ =*.45*	τ =*.40*	τ =*.35*	τ =*.30*	τ =*.25*	τ =*.20*	τ =*.15*	τ =*.10*	τ =*.05*
Variable:										
CONSTANT	-.604	-.612	-.627	-.652	-.660	-.661	-.674	-.718	-.731	-.598
	(.034)[a]	(.026)[a]	(.027)[a]	(.038)[a]	(.029)[a]	(.036)[a]	(.027)[a]	(.034)[a]	(.061)[a]	(.021)[a]
URBAN	.062	.075	.085	.110	.116	.040	.043	.100	.061	.105
	(.074)	(.060)	(.056)	(.082)	(.069)[c]	(.071)	(.055)	(.076)	(.081)	(.054)[c]
DELTA	-.166	-.168	-.215	-.190	-.235	-.226	-.233	-.176	-.187	-.159
	(.068)[b]	(.054)[a]	(.054)[a]	(.079)[b]	(.062)[a]	(.078)[a]	(.058)[a]	(.069)[b]	(.080)[b]	(.048)[a]
ln INFTECH[d]	-.048	-.047	-.048	-.048	-.047	-.026	-.019	-.029	-.007	-.046
	(.030)	(.023)[b]	(.021)[b]	(.028)[c]	(.022)[b]	(.024)	(.017)	(.016)[c]	(.027)	(.022)[b]
ln OTHER[d]	.055	.064	.032	.055	.056	.034	.043	.031	.036	.038
	(.048)	(.037)[c]	(.037)	(.055)	(.044)	(.052)	(.041)	(.059)	(.067)	(.036)
N	60	60	60	60	60	60	60	60	60	60
R^2	.153	.172	.185	.198	.225	.241	.264	.302	.341	.297

Notes:
Standard errors in parentheses.
N = Number of observations.
[a] Significant at the .01 level
[b] Significant at the .05 level
[c] Significant at the .10 level
[d] Log of Gram-Schmidt orthogonalized value of variable

Table 3
OLS And Quantile Parameter Estimates:
Equation (2) with Interactions

Specification:	*OLS* [e]	τ =.95	τ =.90	τ =.85	τ =.80	τ =.75	τ =.70	τ =.65	τ =.60	τ =.55
Variable:										
CONSTANT	-.581	-.408	-.429	-.466	-.469	-.475	-.529	-.549	-.569	-.581
	(.021)^a	(.024)^a	(.029)^a	(.033)^a	(.039)^a	(.033)^a	(.047)^a	(.048)^a	(.034)^a	(.032)^a
URBAN	.126	.027	.091	.093	.093	.095	.154	.118	.138	.152
	(.047)^a	(.033)	(.033)^a	(.039)^a	(.051)^c	(.046)^b	(.103)	(.110)	(.078)^c	(.075)^b
DELTA	-.171	-.135	-.133	-.147	-.144	-.140	-.181	-.167	-.164	-.157
	(.039)^a	(.033)^a	(.032)^a	(.054)^a	(.062)^b	(.051)^a	(.087)^b	(.090)^c	(.067)^b	(.063)^a
ln INFTECH^d	.016	-.025	.042	-.019	-.019	-.019	-.014	-.006	.003	.011
	(.037)	(.016)	(.033)	(.036)	(.045)	(.039)	(.062)	(.061)	(.043)	(.041)
ln OTHER^d	-.020	.006	-.059	-.006	-.002	.005	-.001	.021	.022	-.013
	(.046)	(.037)	(.032)^c	(.067)	(.075)	(.060)	(.083)	(.083)	(.059)	(.058)
ln INFTECH	-.120	-.101	-.167	-.107	-.106	-.107	-.117	-.096	-.105	-.127
$\times$ URBAN	(053)^b	(.020)^a	(.036)^a	(.042)^b	(.053)^b	(.048)^b	(.118)	(.097)	(.069)	(.075)^c
ln INFTECH	-.025	-.118	-.029	-.118	-.119	-.123	-.046	-.064	-.059	-.056
$\times$ DELTA	(.021)	(.032)^a	(.043)	(.065)^c	(.075)	(.061)^b	(.098)	(.103)	(.072)	(.082)
N	60	60	60	60	60	60	60	60	60	60
R^2	.120	.238	.233	.221	.219	.210	.189	.190	.188	.196

Notes:
Standard errors in parentheses.
N = Number of observations.
[a] Significant at the .01 level
[b] Significant at the .05 level
[c] Significant at the .10 level
[d] Log of Gram-Schmidt orthogonalized value of variable
[e] Robust standard errors

Table 3—continued
OLS And Quantile Parameter Estimates:
Equation (2) with Interactions

Specification:	τ =.50	τ =.45	τ =.40	τ =.35	τ =.30	τ =.25	τ =.20	τ =.15	τ =.10	τ =.05
Variable:										
CONSTANT	-.589	-.597	-.604	-.611	-.642	-.654	-.668	-.703	-.716	-.741
	(.028)^a	(.033)^a	(.029)^a	(.020)^a	(.030)^a	(.038)^a	(.027)^a	(.034)^a	(.074)^a	(.062)^a
URBAN	.103	.110	.118	.043	.067	.078	.092	.128	.140	.166
	(.067)	(.080)	(.070)^c	(.043)	(.071)	(.063)	(.038)^b	(.045)^a	(.088)	(.080)^b
DELTA	-.153	-.146	-.187	-.183	-.228	-.222	-.237	-.202	-.200	-.175
	(.055)^b	(.066)^b	(.058)^a	(.042)^a	(.055)^a	(.069)^a	(.047)^a	(.064)^a	(.085)^b	(.080)^b
ln INFTECH^d	.014	.018	.021	.024	.027	.013	.019	.007	-.012	.017
	(.036)	(.042)	(.037)	(.024)	(.042)	(.052)	(.029)	(.033)	(.061)	(.056)
ln OTHER^d	-.002	-.002	-.001	.006	-.008	-.007	-.007	-.007	-.007	-.007
	(.051)	(.061)	(.054)	(.036)	(.054)	(.069)	(.041)	(.053)	(.118)	(.088)
ln INFTECH × URBAN	-.104	-.108	-.111	-.080	-.086	-.071	.077	-.065	-.047	-.075
	(.066)	(.079)	(.070)	(.039)^b	(.074)	(.077)	(.036)^b	(.040)	(.072)	(.063)
ln INFTECH × DELTA	-.068	-.072	-.127	-.136	-.045	.039	.016	.028	.039	.011
	(.073)	(.089)	(.081)	(.060)^b	(.092)	(.089)	(.064)	(.092)	(.113)	(.055)
N	60	60	60	60	60	60	60	60	60	60
R^2	.207	.218	.230	.231	.251	.272	.301	.339	.378	.339

Notes:
Standard errors in parentheses.
N = Number of observations.
[a] Significant at the .01 level
[b] Significant at the .05 level
[c] Significant at the .10 level
[d] Log of Gram-Schmidt orthogonalized value of variable

Table 4
OLS And Quantile Parameter Estimates
Equation (3):
Mississippi County Income Growth and Inequality

Specification:	*OLS* [d]	τ =.95	τ =.90	τ =.85	τ =.80	τ =.75	τ =.70	τ =.65	τ =.60	τ =.55
Variable:										
CONSTANT	.421	1.28	1.21	.932	.736	.617	.303	.288	.325	.551
	(.318)	(.235)^a	(.558)^b	(.470)^b	(.447)	(.415)	(.378)	(.269)	(.314)	(.361)
I90	.006	-.039	-.035	-.018	-.009	-.001	.017	.018	.015	.004
	(.016)	(.011)^a	(.031)	(.024)	(.023)	(.022)	(.019)	(.014)	(.016)	(.019)
$ln\ \varphi$	-.419	-.651	-.557	-.436	-.493	-.385	-.289	-.289	-.323	-.263
	(.094)^a	(.114)^a	(.261)^b	(.190)^b	(.188)^b	(.194)^b	(.172)^c	(.119)^b	(.123)^b	(.132)^b
URBAN	.520	.224	.025	-.080	.369	.328	.392	.395	.530	.552
	(.163)^a	(.095)^b	(.175)	(.172)	(.177)^b	(.178)^c	(.174)^b	(.133)^a	(.153)^a	(.175)^a
DELTA	.171	.309	.417	.447	.324	.285	.184	.184	.173	.140
	(.119)	(.074)^a	(.189)^b	(.198)^b	(.177)^c	(.161)^c	(.141)	(.148)	(.109)	(.121)
URBAN	.805	.082	-.331	.514	.519	.452	.579	.586	.879	.867
$\times$ ln φ	(.316)^a	(.199)	(.313)	(.302)^c	(.358)	(.347)	(.329)	(.263)^b	(.276)^a	(.316)^a
DELTA	.296	.503	.603	.660	.534	.435	.277	.276	.274	.211
$\times$ ln φ	(.161)^c	(.134)^a	(.338)^c	(.276)^b	(.255)^b	(.241)^c	(.214)	(.148)^c	(.159)^c	(.175)
N	82	82	82	82	82	82	82	82	82	82
R^2	.273	.305	.223	.194	.174	.155	.152	.156	.154	.143

Notes:
Standard errors in parentheses.
N = Number of observations.
[a] Significant at the .01 level
[b] Significant at the .05 level
[c] Significant at the .10 level
[d] Robust standard errors

Table 4—continued
OLS And Quantile Parameter Estimates
Equation (3):
Mississippi County Income Growth and Inequality

Specification:	τ =.50	τ =.45	τ =.40	τ =.35	τ =.30	τ =.25	τ =.20	τ =.15	τ =.10	τ =.05
Variable:										
CONSTANT	.258	.419	.359	.308	.065	.069	.303	.354	.468	.554
	(.401)	(.462)	(.661)	(.625)	(.431)	(.253)	(.406)	(.347)	(.565)	(.306)[c]
I90	.018	.008	.011	.011	.019	.019	.004	.001	-.007	-.013
	(.021)	(.024)	(.034)	(.032)	(.022)	(.013)	(.021)	(.018)	(.028)	(.013)
ln φ	-.284	-.321	-.324	-.368	-.461	-.473	-.535	-.518	-.567	-.589
	(.145)[c]	(.153)[b]	(.212)	(.203)[c]	(.142)[a]	(.078)[a]	(.128)[a]	(.111)[a]	(.207)[a]	(.134)[a]
URBAN	.471	.512	.662	.703	.787	.593	.642	.499	.524	.537
	(.204)[b]	(.217)[b]	(.259)[b]	(.276)[a]	(.197)[a]	(.118)[a]	(.203)[a]	(.076)[a]	(.115)[a]	(.067)[a]
DELTA	.199	.209	.178	.120	.050	.065	.069	.072	.070	.067
	(.139)	(.157)	(.218)	(.219)	(.121)	(.069)	(.108)	(.072)	(.122)	(.077)
URBAN	.757	.788	1.14	1.19	1.31	1.04	1.03	.819	.811	.793
$\times$ ln φ	(.368)[b]	(.401)[c]	(.456)[b]	(.476)[b]	(.327)[a]	(.194)[a]	(.325)[a]	(.143)[a]	(.227)[a]	(.165)[a]
DELTA	.278	.296	.287	.220	.139	.167	.208	.228	.222	.212
$\times$ ln φ	(.204)	(.223)	(.308)	(.115)[c]	(.183)	(.105)	(.167)	(.117)[c]	(.205)	(.143)
N	82	82	82	82	82	82	82	82	82	82
R^2	.131	.123	.114	.117	.138	.170	.188	.236	.301	.372

Notes:
Standard errors in parentheses.
N = Number of observations.
[a] Significant at the .01 level
[b] Significant at the .05 level
[c] Significant at the .10 level

References

Aghion, Philippe, Eve Caroli and Cecilia Garcia-Penalosa. "Inequality and Economic Growth: The Perspective of the New Growth Theories", *Journal of Economic Literature*, 37(4), December 1999: pp. 1615 - 1660.

Atkinson, Robert D., and Randolph H. Court. *The New Economy Index: Understanding America's Economic Transformation*, Progressive Policy Institute Technology, Innovation and New Economy Project, Washington DC. November 1998.

Atkinson, Robert D., Randolph H. Court, and Joseph M. Ward. *The New Economy Index: Benchmarking Economic Transformation in the States*, Progressive Policy Institute Technology, Innovation and Economy Project, Washington DC, July 1999.

Cameron, Colin A. and Frank A.G. Windmeijer. "An R-squared Measure of Goodness of Fit for Some Common Nonlinear Regression Models", *Journal of Econometrics*, 77(4), April 1997: pp. 329 - 342.

Card, David and John Dinardo. "Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles", *Journal of Labor Economics*, 20(4), October 2000: pp. 733 - 783.

Cole, Harold L., George J. Mailath, and Andrew Postlewaite. "Incorporating Concern for Relative Wealth Into Economic Models", *Federal Reserve Bank of Minneapolis Quarterly Review*, 19(3), Summer 1995: pp. 12 - 21.

Cook, Peggy J. and Karen L. Mizer. *The Revised ERS County Typology: An Overview*, Economic Research Service, Rural Development Research Report Number 89, United States Department of Agriculture, 1994.

Deininger, Klaus and Lyn Squire. "A New Data Set Measuring Income Inequality", *World Bank Economic Review*, 10(3), Fall 1996: pp. 565 - 591.

Doolittle, Larry and Jerry Davis. "Social and Economic Change in the Mississippi Delta: An Update of Portrait Data", Social Research Report Series 96-2, Social Science Research Center, Mississippi State University, May 1996.

Galor, Oded and Omer Moav. "Ability-Biased Technological Transition, Wage Inequality, and Economic Growth", *Quarterly Journal of Economics*, 115(2), May 2000: pp. 469 - 497.

Gloom, Gerhard. "Inequality, Majority Voting, and the Redistributive Effects of Public Education Funding", *Pacific Economic Review*, 9(2), June 2004: pp. 93 - 101.

Johnson, George E. "Changes in Earnings Inequality: The Role of Demand Shifts", *Journal of Economic Perspectives*, 11(2), Spring 1997: pp. 41 - 54.

Koenker, Roger and Kevin F. Hallock. "Quantile Regression", *Journal of Economic Perspectives*, 15(4), Fall 2001: pp. 143 - 156.

Koenker, Roger and Jose A.F. Machado. "Goodness of Fit and Related Inference Processes for Quantile Regression", *Journal of the American Statistical Association*, 94(448), December 1999: pp. 1296 - 1310.

Koenker, Roger W. and Gilbert Bassett Jr. "Regression Quantiles", *Econometrica*, 46(1), January 1978: pp. 33 - 50.

Li, Hongyi and Heng-Fu Zou. "Income Inequality is Not Harmful for Growth: Theory and Evidence", *Review of Development Economics*, 2(3), October 1998: pp. 318 - 334.

Mankiw, N. Gregory, David Romer, and David N. Weil. "A Contribution To The Empirics Of Economic Growth", *Quarterly Journal of Economics*, 101(2), May 1992: pp. 407 - 437.

Mello, Marcelo and Roberto Perrelli. "Growth Equations: A Quantile Regression Exploration", *Quarterly Review of Economics and Finance*, 43(4), Autumn 2003: pp. 643 - 667.

Oliner, Stephen D. and Daniel E. Sichel. "The Resurgence of Growth in the Late 1990s: Is Information Technology the Story?", *Journal of Economic Perspectives*, 14(4), Fall 2000: pp. 3 - 22.

Persson, Torsten and Guido Tabellini. "Is Inequality Harmful for Growth?" *American Economic Review*, 84(3), Fall 1994: pp. 600 - 621.

Saville, David J. and Graham R. Wood. *Statistical Methods: The Geometric Approach*, 1991, Springer-

Verlag, New York.

Vanhoudt, Patrick. "An Assessment of the Macroeconomic Determinants of Inequality", *Applied Economics*, 32(10), June 2000: pp. 877 - 883.

BluePrint Mississippi, Mississippi Economic Council, 2004.

U.S. Census Bureau, *County and City Data Book:* 2000, 13th Edition, U.S. Government Printing Office, Washington, DC.

U.S. Census Bureau, County Business Patterns 2000 - 2001, U.S. Government Printing Office, Washington, DC, 2003.